AN EXAMINATION OF THE STABILITY OF FORECASTING IN FAILURE PREDICTION MODELS

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ABSTRACT

The main focus of this study is an empirical examination of the stability of company failure prediction models based on accounting information. Stability of forecasting in failure prediction models is tested using industry relative ratios and unadjusted ratios. Three homogeneous economic periods are defined : expansion, recession, and recovery. The stability and quality of forecasting models developed in these three different economic environments is tested using the industry relative ratios previously derived. The study also compares the stability of forecasting of both the industry-specific models and the aggregate model for each of the five years before failure. Specific industries include Contracting, General-Engineering, Textile, Other Manufacturing, and Miscellaneous. Finally, the ability of economy-wide indicators and year-dummies proxying calendar events to predict failure is examined.

Industry adjusted and unadjusted ratio models, business cycles models (adjusted and unadjusted ratios) and specific industry models are reported. Each model is developed using multivariate discriminant analysis. An examination of the stability of forecasting in failure prediction models in terms of the classification accuracy, proportional chance criterion, expected cost, relative cost ratios, and Conover [1971] T test is performed. Finally, comparison graphs for each model are plotted.

Industry relative (mean) ratios were preferred to unadjusted ratios because they reduce the heterogeneity of companies' data. This results in improved stability of forecasting both in the within-sample (ex post) and out-of-sample (ex ante) context. Subsequent, industry relative ratios are used to control for industry differences and different economic environments are used to control for time-inconsistency. The empirical findings of the study are that use of industry relative (mean and median) ratios and business cycles provides more stability and gives better predictive ability than use of unadjusted ratios and uncontrolled economic environments. In general, segmentation of the sample according to industry produced models that performed

better than ones based on aggregate data across industries. Because each industry has different financial characteristics we conclude that industry-specific models should be developed if data is available. We find that industry specific and different economic conditions models are robust with respect to variation in prior probability and misclassification costs. In the context of failure prediction, accounting information appears to be more useful than macro-economic variables. The 4 macro-economic and 11 year-dummy variables are shown not to play an important role, adding only marginal discriminating power to the models.

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ABBREVIATIONS

IRR1 = Industry Mean Ratios

IRR2 = Industry Median Ratios

UR = Unadjusted Ratios

URAG = Unadjusted Ratios Aggregate Model

URB1 = Unadjusted Ratios in the expansionary phase of the business cycle

URB2 = Unadjusted Ratios in the recessionary phase of the business cycle

URB3 = Unadjusted Ratios in the recovery phase of the business cycle

IRR1AG = Industry Mean Ratios Aggregate Model

IRR1B1 = Industry Mean Ratios in the expansionary phase of the business cycle

IRR1B2 = Industry Mean Ratios in the recessionary phase of the business cycle

IRR1B3 = Industry Mean Ratios in the recovery phase of the business cycle

IRR2AG = Industry Median Ratios Aggregate Model

IRR2B1 = Industry Median Ratios in the expansionary phase of the business cycle

IRR2B2 = Industry Median Ratios in the recessionary phase of the business cycle

IRR2B3 = Industry Median Ratios in the recovery phase of the business cycle

Con = Contracting Industry

GE = General Engineering Industry

Tex = Textile Industry

Other = Other Manufacturing Industry

Mis = Miscellaneous Industry

SBA = Small Business Administration

RMA = Robert Morris Associates

LDA = Linear Discriminant Analysis

QDA = Quadratic Discriminant Analysis

MDA = Multivariate Discriminant Analysis

OTC = Over - the - Counter

RPA = Recursive Partitioning Algorithm

NA = Non-parametric Approach

NLV	=	Net Liquidation Value
CFFO	=	Cash Flow From Operations
GPL	=	General Price Level
FASB	=	Financial Accounting Securities Boarding
SEC	=	Securities Exchange Committee
HC	=	Historical Cost
SPL	=	Specific Price-Level Adjusted
USDC	=	United States Department of Commerce
NBER	=	National Bureau of Economic Research
SSERD	=	Sydney Stock Exchange Research Department
BC	=	Business Cycles
GNP	=	Gross National Product
SIC	=	Standard Industry Classification
SEIC	=	Stock Exchange Industry Classification
BF	=	Before Failure

Chapter 1. Introduction

1.1 Historical Perspective

During the past two decades, many authors have attempted to develop robust corporate failure prediction models. The intention of these studies has been to explain the causes and symptoms of bankruptcy and to provide useful data to investors for reducing the risk of investment, to lenders as reference for finance and credit, to regulators for assistance in public policy making, to decision makers for directing management improvement, to auditors to provide a basis for opinions, and to other groups as well. Early financial analysts used to distinguish between failed and non-failed firms using univariate comparisons of financial ratios. Beaver [1966] was the first scientific study to compare group means for 30 financial ratios. However, two years later, Altman [1968] moved researchers away from the univariate use of ratios. He applied multivariate statistical methods able to deal with combinations of two or more variables. This innovation resulted in the increasing use of multivariate discriminant analysis [MDA]. Later studies, Edmister [1972]; Deakin [1972]; Blum [1974]; Libby [1975]; and Taffler [1977] all used MDA to develop their individual models. To date there are probably in excess of 100 studies that have applied MDA to the prediction and analysis of corporate failure. Several more recent studies for large firms see Martin [1977]; Ohlson [1980]; Mensah [1983]; Zmijewski [1984]; Casey and Bartczak [1985]; Zavgren [1985, 1988]; for small firms see Keasey and Watson [1987b]; and Storey et al. [1987] have used logit and probit techniques which provide a conditional probability of an observation belonging to a certain class, given the values of the independent variables for that observation. Another interesting extension of the logit techniques has been provided by Lau [1982] use of a multi-nomial logit analysis to categorize four different states of financial distress rather than the simply binary bankrupt and non-bankrupt. Most recently, both Marais, Patell, and Wolfson, [1984] and Frydman, Altman, and Kao [1985] used recursive partitioning analysis. The field is still innovating Barniv and Raveh [1989] who used non-parametric analysis have presented an impressive classification tool.

All of these previous studies report success in using individual firms' financial ratios to distinguish between bankrupt and non-bankrupt firms. Although some of these models have met certain statistical success in both explaining and predicting bankruptcy, the within-sample classification results using statements one year prior to failure are somewhat inconsistent with those of the out-of-sample. The instability of predictive ability between ex post (within-sample) and ex ante (out-of-sample) results is perhaps the most problematic issue in the field of corporate failure prediction. Moyer [1977], Mensah [1984] and Wood and Piesse [1987] have shown that bankruptcy prediction models are not stable over time. That is, the estimated statistical coefficients change from time period to time period. A possible reason is that accounting ratios are unlikely to be stable throughout such a time period and across so many different industries due to changes in inflation, interest rates, and phases of the business cycle which may be responsible for the differences in classification results from estimation to forecast periods. Therefore, there are a number of ways to cope with this instability problem. For example, Dambolena and Khoury [1980] used the variation of the ratios instead of their values as a measure of their stability. Altman and Izan [1984], Izan [1984], Platt and Platt [1990] proposed using industry relative ratios to control industry variation. Using a sample of Australian and American companies they presented stable classification results between within-sample and out-of-sample. Mensah [1984] used phases of a business cycle to deal with the variation of American companies in different economic environments and proved that accuracy and structure of classification models differed across different economic conditions and industrial sectors. This thesis focuses on this key issue of the stability of predictive classification between ex post (within-sample) and ex ante (out-of-sample). In this thesis, use of industry relative ratios and consideration of phases of business cycles simultaneously to control time series and across-industries instability problems are investigated as the way to develop failure prediction models. Another theme of the investigation is to adjust for industry-specific differences in the aggregate model.

1.2 Objective of the Research

The objective of this study is to develop a class of stable business failure prediction models. To examine the effects on stability of forecasting between ex post and ex ante samples using industry relative ratios compared to unadjusted ratios. To investigate models based on different phases of the business cycle, specifically, attention is focused on the interaction of industry and business cycle effects. In addition, the study examines the difference between specific industry models and an aggregate model. The specific objectives of the study are:

1: To test if the stability of business failure prediction between ex post and ex ante samples can be improved over time and across industries by using industry relative (mean and median) ratios.

2: To test if the stability of business failure prediction can be improved with respect to different phases of the business cycle: expansion, recession, and recovery using industry relative (mean), industry relative (median), and unadjusted ratios as compared to an aggregate model.

3. To test if the stability of business failure prediction results can be improved by using an industry-specific as compared to an aggregate model.

The principal objective of this study is to examine whether the stability of a model forecasting business failure/distress can be improved over time and across industries using industry relative ratios as opposed to unadjusted ratios. Furthermore, the stability of forecasting with different phases of business cycles is also a major issue in examining failure/distress prediction models. It is frequently believed that financial characteristics are different for each different type of industry over time. The stability of a prediction model developed from the sample of one industry may not be appropriate when applied to another industry. Therefore, industry-specific models are developed on the basis of 41 financial ratios, 4 macro-economic variables, and 11 year dummy variables. This study will also present the results of a univariate analysis and tests of the normality of the financial ratios used.

1.3 Importance of the Research

This study contributes to the existing research in several ways. First, this study highlights whether industry relative (mean and median) ratios can improve the stability of a prediction model over time and across industry. Edmister [1972], Sudarsanam [1981], and Sudarsanam and Taffler [1985] have found that the mean values of some accounting ratios vary from industry to industry. Izan [1984] suggested the use of industry relative (median) ratios to reduce the impact of industry effect; Altman [1983, 1984] recommended that an adjustment of ratios is required to take into account industry differences and heterogeneous nature of failed firms. Foster [1986] discusses the use of this approach to control industry differences in the financial ratios. Platt and Platt [1990] found that using industry relative (mean) ratios can yield more stable forecasts of financial status across time periods. The Platt and Platt results are an important motivation for developing a class of appropriate models and for examining the stability of forecasting failure prediction model.

Second, this study concentrates on different economic environments which can be expected to have an impact on the stability of corporate failure prediction models. Mensah [1984] stated that the accuracy and structure of corporate predictive models differed across different economic environments. The accuracy of the model may improve if the models are re-examined over different time periods, such as expansionary, recessionary, and recovery periods. Different prediction models seem appropriate for companies in different industrial sectors even for the same economic environment. This is because of a lack of sufficient data within a time period, say recessionary period, for each specific industries. There are a number of ways around the stability problems over time across industries. One is to estimate industry-specific models. Another is to adjust for industry specific-differences in the aggregate model. We establish that the best and more appropriate way to develop a class of stable failure/distress prediction model is the use of industry relative ratios and the consideration of separate economic environments simultaneously.

Third, several researchers have concentrated their failure prediction effort on industry-specific models. For example, Meyer and Pifer [1970] and Sinkey [1975] focused on commercial banks, Altman [1973] on railroads, Mason and Harris [1979] on construction companies, Collins [1980] on credit unions, Pantalone and Platt, [1987b]; and Korobow, et al., [1976] on commercial banks, Pantalone and Platt [1987a] and Barth et al., [1985] on thrift failure. Platt and Platt [1990] state that focusing on one industry is analogous to using industry relative ratios in samples including several industries. This study presents a comparison between the empirical result of using an industry relative ratio aggregate model and single industry model (Textile Industry).

Fourth, we investigate whether the prediction model developed from the sample of one industry may not be appropriate to apply to another industry. For example, companies in contracting may fail for reasons different from those in the Textile industry. Therefore, it may be possible to improve the accuracy of the prediction of financial failure by taking into account industry differences. The sample used to develop the discriminant functions for each specific industry is based on the 16 broad classification industrial sectors.

Fifth, several authors (Dambolena and Khoury, [1980] and Rose, Andrews, and Giroux, [1982]) have suggested incorporating a macro-economic variable into the study of failure prediction. Cressy [1991] used the economy-wide year-dummies on the potential for small firm bankruptcy to examine the differential impact of time or more precisely of temporal economy-wide effects on bankruptcy probabilities. Not too many previous attempt has been made to explore the effects of macro-economic variables on individual large firm bankruptcies. This study also concentrates on using four traditional macro-economic variables (interest rate, annual inflation rate, real GNP, and industrial production) as well as year-dummies in the development of industry-specific failure prediction models.

Sixth, realistic prior probabilities are estimated from Department of Trade Companies Annual Reports (1974-1985) with consideration of the costs of classification errors. Also proportional chance criteria, relative cost ratios, and Conover [1971] T test are used for significance tests and model efficiency measure.

In conclusion, there is a need to develop a class of stable predictive models. Using UK financial ratios, macro-economic, and dummy variables as presented above, forecasting stability can then be examined with respect to the use of industry relative ratios and unadjusted ratios, separate business cycles and industry-specific models. Specifically, this study is intended to investigate the predictive ability of failure prediction models

1.4 Hypotheses of the Research

Corporate failure prediction models are developed based on financial ratios. The independent variables to be used in model development fall into three groups. (1) Models are developed from each set of individual financial ratios both with the industry relative ratios and unadjusted ratios. (2) Models are developed based on three business cycles using industry relative (mean and median) ratios and unadjusted ratios as compared an aggregate model. (3) Models are developed with 41 financial ratios, macro-economic variables, year dummy variables for each industry-specific and the aggregate samples.

The first set of comparisons analyses models are developed with industry relative ratios and unadjusted ratios in the ex ante sample. The related hypotheses can be stated below :

H_1: There is no difference in the predictive abilities of financial ratios between the industry mean ratios (**IRR1**) and the model of unadjusted ratios (**UR**) in the ex ante sample.

H_2: There is no difference in the predictive abilities of financial ratios between the industry median ratios (**IRR2**) and the model of unadjusted ratios (**UR**) in the ex ante sample.

H_3: There is no difference in the predictive abilities of financial ratios between the industry mean ratios (**IRR1**) and the model of industry median ratios (**IRR2**) in the ex ante sample.

The second set of comparisons analyses models are developed based on business cycles in the expansionary phase. The related hypotheses can be stated below.

H_4: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of unadjusted ratios in the expansionary phase (**URB1**) of the business cycle.

H_5: There is no difference in the predictive abilities of financial ratios between the industry mean aggregate model (**IRR1AG**) and the model of industry mean ratios in the expansionary phase (**IRR1B1**) of the business cycle.

H_6: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry mean ratios in the expansionary (**IRR1B1**) phase of the business cycle.

H_7: There is no difference in the predictive abilities of financial ratios between the industry median aggregate model (**IRR2AG**) and the model of industry median ratios in the expansionary phase (**IRR2B1**) of the business cycle.

H_8: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry median ratios in the expansionary phase (**IRR2B1**) of the business cycle.

The third set of comparisons analyses models are developed based on business cycles in the recessionary phase. The related hypotheses can be stated below.

H_9: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of unadjusted ratios in the recessionary phase (**URB2**) of the business cycle.

H_{10}: There is no difference in the predictive abilities of financial ratios between the industry mean aggregate model (**IRR1AG**) and the model of industry mean ratios in the recessionary phase (**IRR1B2**) of the business cycle.

H_{11}: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry mean ratios in the recessionary phase (**IRR1B2**) of the business cycle.

H_{12}: There is no difference in the predictive abilities of financial ratios between the industry median aggregate model (**IRR2AG**) and the model of industry median ratios in the recessionary phase (**IRR2B2**) of the business cycle.

H_{13}: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry median ratios in the recessionary phase (**IRR2B2**) of the business cycle.

The fourth set of comparisons analyses models are developed based on business cycles in the recovery phase. The related hypotheses can be stated below.

H_{14}: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of unadjusted ratios in the recovery phase (**URB3**) of the business cycle.

H_{15}: There is no difference in the predictive abilities of financial ratios between the industry mean aggregate model (**IRR1AG**) and the model of industry mean ratios in the recovery phase (**IRR1B3**) of the business cycle.

H_{16}: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry mean ratios in the recovery phase (**IRR1B3**) of the business cycle.

H_{17}: There is no difference in the predictive abilities of financial ratios between the industry median aggregate model (**IRR2AG**) and the model of industry median ratios in the recovery phase (**IRR2B3**) of the business cycle.

H_{18}: There is no difference in the predictive abilities of financial ratios between the unadjusted ratios aggregate model (**URAG**) and the model of industry median ratios in the recovery phase (**IRR2B3**) of the business cycle.

The fifth set of comparisons analyses models are developed with different industry-specific and the aggregate samples. The related hypotheses can be stated below.

H_{19}: There is no difference in the predictive abilities of financial ratios, macro-economic and year dummy variables between the unadjusted ratios aggregate model and the model of **Contracting (Con)** industry samples.

H_{20}: There is no difference in the predictive abilities of financial ratios, macro-economic and year dummy variables between the unadjusted ratios aggregate model and the model of **General-Engineering (GE)** industry samples.

H_{21}: There is no difference in the predictive abilities of financial ratios, macro-economic and year dummy variables between the unadjusted ratios aggregate model and the model of **Textile (Tex)** industry samples.

H_{22}: There is no difference in the predictive abilities of financial ratios between the industry relative ratios model and the model of a single (Textile) industry sample.

H_{23}: There is no difference in the predictive abilities of financial ratios, macro-economic and year dummy variables between the unadjusted ratios aggregate model and the model of **Other Manufacturing (Other)** industry samples.

H_{24}: There is no difference in the predictive abilities of financial ratios, macro-economic and year dummy variables between the unadjusted ratios aggregate model and the model of **Miscellaneous (Mis)** industry samples.

The statistics for the comparisons are presented in chapter 7-9 with discussion of the results. Conclusions are stated in chapter 10.

Chapter 7

	Ex Ante Sample Predictive Ability UR	IRR1	IRR2
UR IRR1 IRR2		H_1	H_2 H_1

Chapter 8

	Expansion Phase Predictive Ability URB1	IRR1B1	IRR2B1
Aggregate URAG IRR1AG IRR2AG	H_4	H_6 H_5	H_8 H_7
	Recession Phase Predictive Ability URB2	IRR1B2	IRR2B2
Aggregate URAG IRR1AG IRR2AG	H_9	H_{11} H_{10}	H_{13} H_{12}
	Recovery Phase Predictive Ability URB3	IRR1B3	IRR2B3
Aggregate URAG IRR1AG IRR2AG	H_{14}	H_{16} H_{15}	H_{18} H_{17}

Chapter 9

	Industry Specific Predictive Ability Con	GE	Tex	Other	Mis
URAG IRR1	H_{19}	H_{20}	H_{21} H_{22}	H_{23}	H_{24}

Con = Contracting, GE = General Engineering, Tex = Textile,
Other = Other Manufacturing, Mis = Miscellaneous

1.5. Limitations of the Research

The limitations of this study are in relation to the nature of data applied and to the sample used. These limitations include:

1. Generalizability of the results is limited to firms from the U.K. the Datastream data base, and the years study from 1974 to 1985.

2. Palepu [1986] suggests that the use of non-random samples makes the reported predictive results unreliable. Nevertheless, in an empirical context Zmijewski [1984] found that, although non-random samples gave rise to biases, the biases did not appear to materially affect the overall classification rates. [Keasey and Watson, 1991]. Therefore, results developed based on the matching approach in this study may differ from the nature of those from a random sample, and so may not be generalizable to all firms on the basis of previous researcher's findings.

3. The accuracy and reliability of the model developed from the use of industry relative ratios is limited to the Datastream data base, the main source of information from U.K., for 16 broadly classified sectors, 41 financial ratios for each firm.

4. Observations were placed into five groups: Contracting, General-Engineering, Textile, Other Manufacturing and Miscellaneous, to derive industry specific models. Consequently, conclusions derived from certain industries may not be applicable elsewhere.

5. The model developed from each specific industry is limited to a sufficient sample of available failed firms. Altman [1983] suggests that 15 to 20 is the minimum number that is required in each group for a reliable statistical analysis to be possible. However, contracting and general-engineering

industries are below by this minimum. Other manufacturing and miscellaneous industries are too broadly defined to represent a single industry. Therefore, this thesis will concentrate on the limited applicability across industries, the textile industry may be the only applicable case to interpret the empirical result comparing the different between the industry relative ratios and a single industry.

Some of these limitations are endemic to this type of research study. Any empirical study is limited in its generalizability unless the study samples cover the complete population.

1.6 Outline of the Chapters

This thesis is separated into ten chapters. Chapter 1 describes the introduction, objectives, importance, limitations, hypotheses of the research, and outline of each chapter.

Chapter 2 presents the methodology of model selection, including the univariate approach, multivariate approach (discriminant analysis), conditional probability approach (logit and probit analysis), classification tree (rule induction) and non-parametric approach, probit, and survival analysis.

Chapter 3 focuses on the methodology of choosing independent variables and dependent variables, incorporating the development of a theory for financial failure, selection of independent ratios, cash flow ratios, macro-economic variables, price level adjustments, the definition of company failure and sample derivation.

Chapter 4 reviews the economic and industry influences, containing the definition of business cycles, industry influences, prediction and stability, how to develop a class of stable industry relative ratios, alternative methods to select industry relative ratios, and developing industry-specific models.

Chapter 5 describes this thesis methodology, research design, sample selection, data analysis-introducing the objective and assumption of multivariate discriminant analysis, evaluating the significance of independent variables, incorporating prior probabilities and misclassification costs, validation techniques.

Chapter 6 introduces the statistical problems of outlier, data distribution and transformation, normality testing, correlation analysis, univariate (profile) analysis, and the industry and economic environmental effects.

In chapter 7, the results of examining the forecasting stability of failure prediction models between the use of industry relative ratios and unadjusted ratios are presented, examines the stability of forecasting between the within-sample and out-of-sample predictions.

Chapter 8 examines three different economic environments (expansionary, recessionary, and recovery periods) between the use of industry relative (mean and median) ratios and unadjusted ratios.

Chapter 9 compares each specific industry model and the aggregate model, and tries to develop each specific industry model.

Chapter 10 is the final chapter. It introduces a summary, and the main conclusions of this thesis, and suggests further areas for research.

Chapter 2. Statistical Approaches to Modelling

2.1 Introduction

Ratio analysis has been used for decades for a number of applications, including credit risk appraisal and failure/distress prediction purposes. There is a substantial body of prior literature employing various statistical methods to develop failure prediction models. To aid understanding such statistical approaches to modelling corporate failure we will review the following techniques for model selection. Table 2.1 displays a summary of the statistical approaches to modelling.

2.2 Univariate Approach

In a univariate approach a single financial ratio is used in the prediction process as an indicator to distinguish the performance of failed firms from non-failed firms. The procedure is to compare the means of ratios of the failed group and of a control group over time (for example, five years prior to failure) to identify the best ratio for failure prediction. One reason for the employment of the univariate approach in the early studies was partly the lack of computer programs that easily calculate more complex statistics. As a result, most authors, at least up until Altman [1968], contributed to the univariate approach. However failure is a multidimensional process which is unlikely to be fully reflected in a single ratio. A single ratio is susceptible to faulty interpretation and potential confusion. Therefore, Altman [1968] was the pioneer in using multivariate methods

Table 2-1 A Summary of the Statistical Approaches To Modelling Corporate Failure

STATISTICAL APPROACHES TO MODELLING

Univariate Approach	Beaver [1966] Tamari [1966] General Comments
Multivariate Discriminant Approach	Early And Recent Studies Altman [1968] Deakin [1972] Blum [1974] Moyer [1977] Lis [1972] Tisshaw [1976] Taffler [1977, 1981,1983] Earl & Marais [1982] El Hennawy & Morris[1983] General Comments
Conditional Probability Approach	Ohlson [1980] Zavgren [1985] Mensah [1983] Storey et al [1987] Keasey & MaGuinness[1990a General Comments
Classification Tree & Nonparametric Approach	Frydman,Altman & Kao[1985] Barniv and Raveh [1989]
Survival Analysis	Keasey & Watson [1990b]

Source: This Study

Beaver [1966] and Tamari [1966] were the two important persons in the univariate analysis from 1960 to date. Among the previous authors, Tamari [1966] analysed the accounts of 28 Israeli manufacturing companies that went bankrupt or nearly bankrupt in the period 1956-1960 and found that for several years prior to their liquidation they had lower ratios than the other industrial companies, and that in most instances the ratios showed a downward trend in the period examined. Especially marked was the drop in the ratio of net worth to total liabilities, net profit to turnover, and the quick ratio.

These findings, however, did not apply completely to all the companies of his sample. The current ratio of one company in his sample had an increase prior to bankruptcy. Only 12 out of the 28 failed companies had all three constituent ratios falling. Tamari [1966] concluded that: "the analyst cannot rely on single ratio alone in measuring the degree of risk". Therefore Tamari constructed an index that can be expressed as a combination of six ratios with the following percentage weightings:

Equity Capital + Reserves / Total Fund	25
Profit trend	25
Current Ratio	20
Value of Production / Inventory	10
Sales / Trade Receivable	10
Value of Production / Working Capital	10

He found that his index provided fairly good criteria for separating failed from non-failed firms. 75% of failed firms had fewer than 35 points on the scale, whereas good performance firms had more than 46 points. The scale comprised ratios from four main financial structures (solvency, profitability, liquidity, and efficiency). Each of them acquired approximately the same weighting in the index and comparison between the failed and non-failed firms indicated a clear discriminating ability.

Discussion: The choice of ratios was based solely on his judgement and without rigourous statistical analysis. However, he did demonstrate the positive association between adverse ratios and business failure.

Beaver [1966, 1968] employed empirical research in business failure prediction using a univariate analysis. Beaver was the first one to be comprehensively concerned with the univariate analysis to predict corporate failure. The objective of Beaver's study [1966] was to examine the predictive usefulness of accounting ratios. He used Moody's Industrial Manual, supplemented by a list of publicly owned firms from Dun and Bradstreet, and produced 79 failed firms in 38 different industries which had failed between 1954 and 1964 compared with a similar 79 non-failed firms. The selection of non-failed firms was based on a paired-sample design according to the same industry, asset size and the corresponding year. The aim of employing the paired-sample design and selecting criteria was to have "control" over the effects of industry, size and economy-wide conditions that otherwise might blur the relationship between accounting ratios and failure.

Some industries have a higher failure risk than others, and it can be shown that larger firms have a lower failure risk than small firms with a smaller capital base. The equally weighted means of 30 financial ratios were collected for five years before failure based on the popularity and success in previous studies. Thirty accounting ratios were then grouped into six "common element" (numerator or denominator) groups and one ratio was selected from each group including: (1). cash flow / total assets, (2). net Income / total assets, (3). total debt / total assets, (4). working capital / total assets, (5). current ratios, and (6). no credit interval. 1 & 2 are profitability, 4 & 5 are liquidity, 3 is solvency, and 6 is efficiency on the basis of the classification as presented. He compared the means of ratios for the failed and non-failed firms over the five years period prior to failure. Beaver called this comparison of means of ratios for two groups a profile (univariate) analysis. It examines if there are observable differences in the ratio mean of the two sets of groups. In general, he used the dichotomous classification technique in terms of Type I and Type II error, and found that financial ratios proved useful in the prediction of bankruptcy and bond default at least five years prior to such failure. He determined that ratios could be used to separate correctly between failed and non-failed firms to a much greater extent than would be possible by random prediction.

The cash flow to total debt ratio was the clearest warning predictor both in the short term and the long term since it had the smallest mis-classification rate. A deterioration in this ratio indicates that a firm is generating decreasing levels of cash flow in relation to the burden of debt it is carrying. Employing this ratio only 10 percent of the failing firms had been classified as non-failing in the first year before failure and 22 per cent in the fifth year before failure. Capital structure ratio ranked second, liquidity ratios third, while turnover ratios were the worst predictors. He was aware of the problem of sample bias and also pointed out that it is desirable to use all available information, not just one piece of evidence at a time, in any model seeking to describe the behaviour of the firm.

Discussion: One limitation of the comparison of the financial ratio means is that it examines only one point of the distribution. Differences between the means could be induced by several extreme observations in either one of the groups examined. Apart from these extreme observations, there could be almost complete overlap in the distributions of the ratios of both groups. Beaver [1966] made several different contributions in this failure prediction:

1. Beaver [1966] defined failure as the inability of a firm to pay its financial obligations as they mature. He claimed that failure occurs if any of the following events are observed: (1) bankruptcy, (2) bond default, (3)

overdrawn bank account, (4) non-payment of a preferred stock dividends. Subsequent research considered bond default as financial distress.

2. The dichotomous classification test was applied to each of the mean or median values of the ratios in the estimation sample to derive a cutoff point. A cut off point was determined to minimize the total misclassifications by visually inspecting the ordered values of each ratio. Each determined cut-off point in the first subgroup (the estimation sample) was used to classify the firms in the second subgroup (the validation sample) as failed or non-failed. The mis-classification rates for five ratios for each of the five years before failure are 13%, 21%, 23%, 24%, and 22%, respectively. The cash flow to total debt and the net income to total assets ratios classified with similar success in each of the three years prior to failure. In his paper, Beaver discussed the success of the dichotomous classification test in terms of Type I and Type II errors. He used a cut-off point to minimize the total number of mis-classifications resulting in different percentages of Type I and Type II errors. In particular, Type I errors (misclassifying failed firms as non-failed) were always more expensive than Type II (misclassifying non-failed firms as failed). Using a mean univariate model implies predicting failure if the ratio is greater than the cut-off point and predicting non-failure if the ratio is less than the cut-off point.

3. Likelihood ratio analysis was used, the probability that an observed value of a ratio would appear if the firm was failed, P(R/F), or non-failed, P(R/E). If the likelihood-odds ratio in favour of failure is greater than (less than) 1, the user of the ratio, will feel that the firm is more (less) likely to fail. The higher (lower) the likelihood ratio, the stronger (lesser) the feeling. If the likelihood ratio is exactly 1, the prior feelings of the user are unchanged after looking at the ratio and the posterior-odds ratio will be numerically equal to the prior-

odds ratio. [Beaver, 1966] suggests that a user after looking at accounting ratios should have grounds for changing his prior feeling.

Although the univariate approach has been subject to some shortcomings, especially a lack of integration of the various ratios, Beaver's model achieved remarkable success in financial failure prediction. However the univariate approach does not create clear signals. Zavgren [1983] observes that different variables can give conflicting predictions, thus the approach cannot give clear indication for decision makers who have to consider several aspects of a company's situation. Furthermore, it seems instinctive that a firm is a multidimensional institution that no single ratio could describe. Beaver suggested that:

> "It is possible that a multi-ratio analysis, using several different ratios and/or rates of change in ratios over time, would predict even better than the single ratios."

2.2.1 General Comments on the Univariate approach

The main limitations of the univariate analysis are listed below:

1. There is no guidance on how to select the initial sample of ratios, i.e. selecting the financial ratios used is based simply on the researcher's perception and the result does not rely on a robust statistical test. As a result, both the consistency between the results of the various studies and the appropriate definition to select the predictors has been criticized.

2. It is not clear how to select a reduced sample of ratios. As the classification of firms takes place on a univariate basis, there is the potential for conflicting classifications from the various ratios because of a lack of consideration of the inter-relationships between ratios. The univariate approach cannot provide a method of reducing a initial large ratio set to a certain number of

representative ratios and so excluded redundant ratios.

3. Most of the univariate studies on failure prediction have not considered how they will be used in practice, or whether the unassisted human decision maker is able to achieve superior predictions [Keasey and Watson 1991].

4. Altman [1968] criticized univariate analysis on the grounds that "a univariate study can only consider the measurements used for group assignments one at a time". The MDA technique has the advantage of considering an entire variable profile of the object characteristics simultaneously rather than sequentially examining its individual characteristics. Hence the univariate approach is unlikely to be fully reflective of the symptom of failure.

2.3 Multivariate Techniques

2.3.1 Discriminant Analysis

Multivariate techniques consider a combination of two or more ratios simultaneously. The classic technique is Multivariate Discriminant Analysis (MDA). MDA shows which ratios are most important in predicting failure, what weights should be attached to the selected ratios, and how the weights should be decided, in developing a single index. In general, MDA classifies a company into one of failed or non-failed groups based on a statistic (Z score) that is a weighted combination of independent variables that best distinguishes failed from non-failed firms. There are many studies to date which have applied MDA to the business failure prediction. These studies are included in the following analysis.

2.3.2 Early and Recent Studies

Altman [1968] was the first to use Multivariate Discriminant Analysis to assess the usefulness of financial ratios as an analytical technique for failure prediction. One of the main advantages of using MDA in failure prediction is the potential of analysing two or more financial characteristics profile of failed and non-failed firms simultaneously rather than sequentially examining its individual financial characteristics. Altman [1968] selected the initial sample including 33 manufacturing firms which failed during the 1946-1965 period and 33 non-failed firms paired based on industry, asset size and the corresponding accounting year from Moody's industrial Manual. The mean asset size of these firms was $6.4 million, with a range of between $1 million and $25.9 million. The failed firms' group was defined as having filed a bankruptcy petition under Chapter X of the National Bankruptcy Act. His interpretation of failure is more limited than that used by Beaver. Twenty-two ratios were then calculated for each firm on the basis of their popularity in the literature and potential relevance to the failure study. These ratios were classified on a prior basis into five standard categories including company liquidity, cumulative profitability, leverage, solvency and activity ratios. From these variables, five ratios were best selected by the stepwise procedure. Altman then built a final multiple discriminant model applying accounting ratios one year prior to failure. The resulting discriminant function Z score was determined as:

$$Z = 0.012 X_1 + 0.014 X_2 + 0.033 X_3 + 0.006 X_4 + 0.999 X_5$$

Z = index indicating whether firm is in potential bankrupt group or non-bankrupt group;

$X_1, X_2, \ldots X_5$ = descriptor variables (financial ratios)

With

X_1 = working capital / total assets

X_2 = retained earnings / total assets

X_3 = EBIT / total assets

X_4 = market value equity / book value of total debt

X_5 = sales / total assets

The variables were ranked by their relative contribution (measured by the standardized discriminant coefficients) as X_3, X_5, X_4, X_2 and X_1 respectively. With

X_3 and X_5 measuring profitability and activity, being the two ratios contributing most to discriminating power. The cut-off point between the failed firms and non-failed firms is Z = 2.67, all firms having a Z score of greater than 2.99 clearly fall into the "non-bankrupt" sector, while those firms having a Z below 1.81 are all bankrupt. Firms attaining Z-score between 1.81 and 2.99 were in the "zone of ignorance" or "grey area". Altman then performed several tests to examine the significance of the model. Variables except sales / total assets were significant at the 0.001 level. The significance test rejected the null hypothesis that the observations came from the same population.

The final criterion used to establish the best model was to observe its accuracy in predicting bankruptcy. A series of six tests were performed. The initial sample of 33 firms in each of the two groups is examined using data one financial statement prior to bankruptcy. The model was extremely accurate in classifying 95 per cent of the total sample correctly for the first year prior to failure. The corresponding results were 83% for the second year. The type I error rate was 6 per cent, while the type II error rate was only 3% for the first year. The classification accuracy of failed firms was worse than that of non-failed firms, and deteriorated rapidly. Altman also examined the predictive ability of financial ratios from the financial statement issued two years prior to failure. Not surprisingly, the predictive ability was less than that for one year prior to failure-the total mis-classification rate was 17 per cent, with a type I error increased greatly from 6 per cent (first year) to 28% and a type II error increased slightly from 3% (first year) to 6%.

Third, for testing potential bias, Altman split his original sample into five different subsets for testing. The t-test of the significance of this results rejected the hypothesis that there was no difference between the groups. To test the discriminant model on secondary samples of failed and non-failed firms, a new 25 failed firms whose asset size range was the same as that of the initial failed group was selected to test the upward bias in the validation sample. Twenty-four of these twenty-five firms were correctly predicted to be failed. The correct classifications were 96%, superior to the initial sample (94%). The second validation sample included 66 non-failed firms which had "suffered temporary profitability difficulties" but did not become failed during 1958-1961. It was selected without regard to asset size. The discriminant model correctly predicted 52 out of the 66 (79 per cent) of the sample firms. The predictive ability dropped significantly to only 48% three years prior to the failure. The t-test for this result was significant at the 0.001 level. This is the only hold-out test that was undertaken by Altman.

Finally, the long-range predictive accuracy of classifying firms for three, four, five years prior to bankruptcy declined rapidly. The results showed that the bankruptcy prediction model proved almost useless more than three years prior to the failure event. Blum [1974, p. 13] has criticized the Altman model because the prediction ability declined to less than 50 per cent three years prior to failure. Altman finally concluded that all of the observed five ratios prior to failure showed a deteriorating trend as failure approached and that the largest change in the majority of ratios occurred between the third and the second years prior to failure.

Comment:

1. A discriminant function for the first year prior to bankruptcy was built and this function was used to examine the predictive ability for two, three, four, and five years prior to failure.

2. Altman's ex-post validation of the model is the only hold out test. It is not a test of the predictive power because prediction requires inter-temporal validation, while explanation restricts only in cross validation test.

3. Joy and Tollefson [1975] argued that Altman's population prior probabilities do not reflect the real-world rates of failed to non-failed firms because Altman compared his results to the 50/50 chance criterion used by Beaver. Altman also does not consider the costs of misclassifying firms.

4. Eisenbeis [1977] pointed out that the distribution of independent variables is not multivariate normal. The two group's dispersion matrices are not equal. The selection of the groups definition, the reduction of dimension, and interpretation of the significance of individual variables were not carefully considered or evaluated by Altman. He did not even test for the univariate normality of his variables.

Beaver [1966], Altman [1968] and other authors adopted financial ratios to assist the failure prediction with medium and large asset size firms, they ignored small firms due to the difficulties of obtaining a data set. A study on failure prediction for small business is Edmister's [1972]. The objective for Edmister was to examine the usefulness of financial ratio analysis for predicting small business failure. A sample of 42 firms which defaulted on small business loans was matched with a sample of non-defaulting firms. The mean total asset size of the firms was $164,940. Three consecutive annual financial statements were available, within the years 1958-1965. 280 similar firms which had submitted only one financial statement prior to when the loan was granted were selected for further tests. Nineteen ratios were initially selected in five different ways, namely: level of ratios, relative level of ratios to the industry average ratios, three year trend of ratios, three year average of ratios, and a combination of relative trend level, upon the basis of either being generally advocated by theorists or because they have been significant predictors of business failure in prior empirical research.

Five hypotheses of ratio analysis were tested by Edmister as follows:

1. A ratio's level is a predictor of small business failure;

2. The relative level of the borrower's ratio to the average ratio of other small businesses in the same industry is predictor of small business failure;

3. The three-year trend of each ratio is a predictor of small business failure;

4. The three year average of each ratio is a predictor of small business failure;

5. The combination of the industry relative trend and the industry relative level for each ratio is a predictor of small business failure.

In order to test all the hypotheses, three sequential years' data were collected from the Small Business Administration [SBA] and from Robert Morris Associates [RMA] during 1954-1969. Using a stepwise discriminant procedure, these 19 ratios were reduced to 7 variables in the final discriminant function. On the estimation sample, the total correctly classified 93% for one year prior to failure; there was a type I error of 15% and a type II error of 5%. Although no hold-out sample was used, he did carry out simulation tests providing the statistical significance of above classification results. For example, variable was not allowed to enter the function if its simple correlation coefficient between a variable and any other variable already in the function was not greater than 0.31.

Comment: Edmister concluded that:

1. One single financial statement is not sufficient for the development of a discriminant model, at least three consecutive financial statements are required for effective analysis of small businesses.

2. The predictive ability of ratio analysis depends upon the choice of analytical method and the selection of ratios;

3. Although Edmister's classification results are quite good, they may be due in part at least to his data transformations (e.g., converting ratios into zero-one variables).

4. Edmister's extensive use of the industry data in a multivariate context is his other contribution. His function should be more stable than those of his predecessors, since the highly correlated variables have been eliminated. However, since financial ratios for small businesses usually are dispersed widely, it is difficult to obtain a meaningful data set without some sort of adjustment.

The purpose of Deakin's [1972] study was to propose an alternative business failure model to the ones developed by either Beaver or Altman. Two criteria were employed. First, Deakin was to capture the best of both of these studies by employing the 14 ratios Beaver used and to search for the linear combination of these ratios with greatest predictive accuracy. Second, a sample of 32 failed matched with 32 non-failed firms on the basis of industry classification, asset size, and year of financial information provided were selected from the years 1964 through 1970. The prediction results for the original sample appear to be an improvement over Altman's model. However, prediction results for a hold-out sample were dramatically lower. Deakin concluded that the application of MDA techniques to accounting data could be used to predict financial failure up to three years prior to the event with a fairly high degree of accuracy.

A second sample of 32 failed firms were combined with a random sample of 32 non-failed firms, drawn from Moody's Industrial Manual for the years 1962-1966. Deakin hoped to improve upon the univariate classification accuracy and employed a discriminant function which incorporated all Beaver's 14 accounting ratios and searched for the linear combination of these ratios with greatest predictive ability. Deakin found that these ratios possessed greatly significant discriminant ability in the first three years prior to failure. The middle year, that is, application of the second year discriminant function, was found to have the greatest prediction power. Mis-classification rate was observed to be high in the fourth and fifth year before failure. Given the relatively small size of his samples, he suggested that further testing is required before a conclusive judgement about his model can be rendered.

Comment: Deakin's model lacks a priori and empirical reasoning, prior probabilities and costs of mis-classification were also ignored altogether and no was attempt made either to test for the normality of ratios or to test for the relationship between them. His analysis uses a different discriminant function for each year and some independent model validation processes. It is hard to generalize the finding because of the small sample size and the statistical limitations. However, in his sample selection, Deakin made no attempt to reduce the dimensionality of his initial ratios.

The purpose of Blum's [1974] study was to develop a failing company model to aid the antitrust division of the Justice Department in assessing the probability of business failure. He selected 115 firms which failed during the years 1954-1968 and 115 non-failed firms paired by industry, sales, employees, and fiscal year. Data were drawn from balance sheets, income statements, and stock market prices for eight consecutive years prior to the year of failure. He demonstrated the firm as a reservoir of liquid assets and used a cash flow model to develop the theoretical framework. Blum selected twelve variables depending on liquidity, profitability, and variability of cash flow framework. Twelve non-ratio variables were used to test a non-ratio version of the model. The model correctly classified failing firms and non-failing firms with an accuracy of approximately 93 to 95 per cent of companies in the hold-out sample at the first year prior to failure, 80 per cent at the second year prior to failure, and 70 per cent at the third, fourth, and fifth years before failure. These classification of the hold-out sample were considered a good indicator of the predictive accuracy of the computed functions. The overall accuracy rates for the fourth, fifth, and sixth years are quite similar. In addition, except for the first year prior, the Type I and Type II errors have relatively stable and realistic values across the three ranges.

Comment:

1. The Type I error was more frequent than the Type II error for the first year prior to failure. The cost of Type II error may be greater than that of Type I error. Also, prior probabilities were not considered and total classification errors was smaller than Beaver's.

2. Blum's model seems to have been mis-specified because it incorporated 12 non-financial ratios which were subjectively classified into three groups, and no attempt was made to reduce the variables or to study the nature of their distribution. Blum also pointed out that some ratios changed over time.

3. Variables were not possibly ranked by their standardized discriminant coefficients because of multicollinearity. His study also has some of the same statistical limitations as the other studies reviewed.

Moyer [1977] re-examined the original Altman's [1968] model and found that model parameters are sensitive to either time span used to develop the model or the firm sizes which were represented in his original samples, or both. His re-examination suggested that only modest parameters were applied to his new data [1965-1975]. Altman's [1968] model is not generally suitable when applied to a sample of larger firms outside the original sample period. Moyer used different time span data set to re-examine the Altman's original model. It was found that somewhat better "explanatory" power could be obtained from the model when Altman's second most important variable, sales / total assets variables, and market equity / book value of debt are eliminated from his model. It could be that the significance of these variables are sensitive to the sample data examined.

Lis [1972] the first UK researcher, developed a 4-variables discriminant function with ratios based on Altman [1968]. He used 30 major quoted manufacturing, construction and retailing firms that failed between 1964 and 1972 and 30 non-failed firms matched by industry, assets size and year. The model is given by the last year prior to failure:

$$Z = 0.063X_1 + 0.092X_2 + 0.57X_3 + 0.0014X_4$$

Where

X_1 = net working capital / total assets
X_2 = earnings before interest and tax / total assets,
X_3 = retained earnings / total assets, and
X_4 = net worth / book value of total debt

His model misclassified one-failed firm and 5 non-failed firms first year prior to failure. His model can predict accurately as far as three years prior to failure.

Comment: Lis was the first author to use MDA approach outside the USA and provide stimulation for further work in the UK. However, the results of his model are subject to the same criticisms as the Altman's model.

Tisshaw [1976] developed a model for predicting failure employing privately owned UK manufacturing companies. His failed sample comprised 31 large privately owned manufacturing companies failing in the 18 month period to June 1976, and each of these firms was loosely matched by size, industry and year end with two "healthy" firms on the Jordan database to provide the solvent group. He carefully selected the 80 financial ratio set and reduced the original set of 80 ratios to a more manageable size applying a conventional stepwise LDA approach to produce the following five ratios:

X_1 = EBIT / average total liability
X_2 = profit before tax / sales
X_3 = net capital employed / total liabilities
X_4 = quick assets / net capital employed, and
X_5 = quick ratio.

By adjusting the cut off point he misclassified only one type I and one type II error. He further recommended adjusting the cut-off in practical application for prior probability odds 1:5. By using approximately 2000 unquoted industrial companies he found that 22% had Z score below the resulting cut-off as failing and a further 11 per cent in a 'grey area'.

Comment: The importance of his study clearly illustrated that the MDA approach for prediction failure can be employed to the much maligned accounts of unquoted companies in the UK. However, he did not validate the discriminant function from the initial sample to the forecast sample. His sample design receives the same criticism as those of previous studies.

Taffler [1977, 1981, 1983]

This UK model was described in Taffler and Tisshaw [1977] in a study of auditor behaviour in the going concern decision area. Failure was defined to include the cases of liquidation, winding-up by court order, entry into receivership and reconstruction with government financial assistance as a distinct choice. A total of 23 companies met this criterion between 1968-1973 as well as satisfying a number of other requirements. The non-failed firms were selected on a random statistical basis because he considered that such an approach produced a better representative sample of the larger population of non-failed firms. He did not incorporate industry and size into the analysis. 61 "healthy" firms' accounts over the five year period 1968-73 which he finally selected a group of 45 non-failed firms. Any ratios were excluded from further analysis when they were still significantly non-normal. Finally he then employed only 50 of the traditional ratios. Taffler used principal component analysis to display five interpretable components measuring: profitability, financial leverage, quick assets, working capital position, working capital turnover. Using a traditional stepwise linear discriminate analysis to procedure a five ratios model as follows:

X_1 = EBIT / initial total assets
X_2 = total liabilities / net capital employed
X_3 = quick assets / total assets
X_4 = working capital / net worth
X_5 = stockturn.

Five ratios derived from each highest factor loading are produced. Taffler made a comparison between the initial sample set (61 "healthy" firms) and later reduced sample set (45 "healthy" firms). He found that the function derived from the latter (restricted set of healthy companies) provides a better discriminant ability, and he then employed on that function. In determining the best cut-off Z score, he used subjective estimates made by investment analysts at a firm of stockbrokers, and reached a ratio of 1:10 for failed and non-failed groups, and of 40:1 for mis-classification costs. Taffler then used the ratio of prior probabilities of group membership to set the cut-off level. He argued that the ultimate decision (to invest or not, to lend or not) will consider the cost, while the Z score model only provided decision makers with a reference point to make their final decision.

Using a Lachenbruch [1967] hold-out test he found that his model classified all but one of the original firms correctly. His model's effectiveness was found to deteriorate rapidly when far away from the failure; only 50 and 35 per cent of failed companies were correctly classified three and four years prior to failure. Tuffer's model appears worse than the original Altman's [1968], but Taffler [1981] raises the stationarity argument in explanation of this poor prior-year predictive power.

Taffler [1983] tested the model's true ex-ante predictive ability using a more recent period from 1969 to 1976. The failed sample included 46 firms which were quoted on the London Stock Exchange as failing in the 8 year period to the end of 1976. The "healthy" firms were matched on 1:1 basis by size and industry but not by year with the latest year available being used. He defined "healthy" firms because a continuing operating firm does not necessarily have a good financial health. Using a traditional stepwise linear discriminant analysis to build the final discriminant model which incorporated 4 ratios were ranked by the Mosteller-Wallace percentage contribution measures in brackets:

X_1 = profit before tax / average current liabilities
X_2 = current assets / total liabilities
X_3 = current liabilities / total assets
X_4 = the no-credit interval

The prior probabilities odds were re-adjusted at 1:7, thus resulting in a cut-off point of -1.95 (Ln 1/7 x 1/1). The model correctly classified 98, 96, 100% of all, failed and non-failed companies of the initial sample. The model was able to classify the failed and non-failed firms correctly up to three years prior to the actual event.

The objective of Earl and Marais [1982] was to develop a Bank of England prediction model by comparing the usefulness of the flow of fund variables with the traditional financial ratios which derived from balance sheet, profit and loss account statement, and sources and funds statement. Using the UK-quoted manufacturing and distribution sectors but excluding construction they selected a group of 38 firms which failed during the period 1974-1977 and 53 randomly selected continuing (not very healthy) companies from the Datastream sample of the top 1,000 UK industrial companies for the period 1973-1977. 47 conventional ratios and 12 constructed from the sources and uses of funds statement were used to develop a linear probability function. The preferred model consisted of the following variables:

X_1 = current assets / gross total assets (liquidity),
X_2 = 1000 / gross total assets in £'000 (size),
X_3 = cash flow (profit before tax + depreciation) / current liabilities, and (profitability)
X_4 = funds flow (funds generated from operations - net increase in working capital) / total liability (long term debt + current liabilities) (funds flow).

The relative contribution in declining order was X_3 (profitability), X_2 (size), X_1 (liquidity) and X_4 (funds flow). The proportions classified correctly 95%. In total representing 92% of the non-failed and 97% of the failed group one year prior to failure. The results two years prior were 86%, 84% and 87%, and a deterioration to 77%, 88% and 67% for the third year before failure. However, this test was carried out on the original sample data and is likely to be upwardly biased; the classification accuracy rates for the second model were 93%, 91% and 97% for the first year, 87%, 82% and 92% for the second year and 84%, 94% and 74% for the third year prior to failure.

These results were compared with the Taffler [1977] and Deakin [1977]. Earl & Marais [1982] computed the coefficients of the latter two models using their data. The comparison revealed that the performance of their models in classifying correctly failed and non-failed firms are better than the models of Taffler and Deakin. In addition, funds flow variable added a considerable amount to the predictive ability of the model.

Comment: Taffler [1984, P. 209] commented that there are a few points in this study which need notice : (1) the Bank of England model highlights the need for the analyst always to consider the percentage of the population labelled failing and to minimise this if his model is to have operational utility, (2) it demonstrates how much care needs to be taken in developing in the development of models, (3) it demonstrates how such techniques have now been tried by Central Banks, (4) it illustrates the vital importance of using validation samples in tests of model efficiency and the misleading conclusions that can arise from the resubstitution approach (ie, using the discriminant function derived from a given sample to classify the firms of the same sample).

The objectives of El Hennawy and Morris [1983] were to test whether the power of failure prediction models might be improved with data one and five years prior to the actual event and to derive macro-economic and industry effects indicators. Data was drawn from the 1955-1974 Department of Trade computerized data bank of company financial statements. 44 manufacturing , construction and distribution businesses which failed between 1960 and 1968, while a similar number of non-failed firms were selected on the basis of general financial soundness. The inter-temporal validation sample of 18 companies, covering the period 1969-1971, and comprising nine failed and nine sound companies. An original set of 96 ratios was reduced to 48 by eliminating those which had missing values, non-normal, and highly correlated variables. A stock market index was selected as a general economic indicator, and a cluster analysis was performed to allocate 19 industries into three broad industry sectors: manufacturing, construction, and distribution. In order to avoid multicollinearity problems the principal components analysis was used and seven factors were produced. The discriminant run produced two five variable models which derived from data relating to both the fifth year and the first year prior to failure. The fifth year function derived from 86 firms had the following Z-Score and variables:

$$Z = -4.86 + 13.50X_1 + 3.11X_2 + 4.803X_3 - 0.97X_4 + 0.68X_5$$

Where

X_1 = profit before interest and tax / total assets (profitability).
X_2 = quick assets (i.e. current assets less stocks) / current liabilities, (liquidity).

X_3 = quick assets / total assets (assets position),
X_4 = quarrying and construction industry dummy, and
X_5 = distribution industry dummy,

measuring profitability, liquidity, assets position and industry.

The second model, based on data of the first year derived from 88 companies, was:

$$Z = -6.17 + 11.43X_1 + 14.07X_2 + 0.55X_3 - 1.57X_4 + 0.98X_5$$

Where

X_1 = operating profit before depreciation (flow of funds) / total assets;
X_2 = long-term debt / net capital employed;
X_3 = current assets / total assets;
X_4 = industry dummy for quarrying and construction;
X_5 = industry dummy for distribution.

measuring profitability, capital gearing, assets position and industry membership. The importance of the constituent variables in each model was assessed by four different methods which were uniform in highlighting the power of the profitability ratio accounting for about three-quarters of the function's discriminating ability. The Lachenbruch U-test, cross-validation and inter-temporal validation approaches were conducted on the fifth and first year data set. Overall classification accuracy for the fifth year model was 91 per cent using the hold-out sample, and 94 per cent using the Lachenbruch U test, 94 and 97 per cent accuracy respectively for the first year model. The authors further claimed that their models could lead to random sample classification rates of 98 and above when the ratios of prior probability odds of 1:10 and 1:7 and of mis-classification costs are taken into account. They conclude that their results compared favourably with those of earlier UK models, the profile of failing company will change as it approaches failure. The authors included an assessment of industry differences, macro-economic variables they found that the macro-economic variables do not appear to contribute any discriminatory power and that industry membership is an important factor. A model derived from the fifth years prior to failure can predict failure at least as well as a model based on information one year before failure.

Comment: The work by El Hennawy and Morris was different from most of the earlier work due to the fact that both on statistical rigour of their study and the care with which it was conducted. It is interesting to note that their work included the general economic and industry dummy indicators. However, Taffler [1984, P. 215] raised a number of questions relating to whether serious bias has been introduced by selecting as sound firms those non-failed firms with high rates of return on capital employed.

2.3.3 General Comments On the Multivariate Studies

In summary, the major studies presented above have generally concluded that certain financial ratios are particularly useful in predicting failure for a period of 1-2 years prior to the actual event and that financial ratios of failing firms change over time and across industries. The significant financial ratios used in each model are somewhat different, the results of hold-out validation testing are more or less ten or more percentage points lower than the model's ex-post results. The problem of unstable financial ratio is prevalent among most multivariate accounting and finance studies. However, all these previous studies evoke different comments. Discriminant Analysis assumes that the ratios are multivariate normally distributed and covariance matrices for the variables are equal for the groups of failed and non-failed firms. Few studies of failure have, however, examined the normal distribution condition. Linear Discriminant Analysis [LDA] should be employed when covariance matrices are equal. Otherwise, Quadratic Discriminant Analysis [QDA] should be applied. Both LDA and QDA are sensitive in their classification accuracies to differences in covariance matrices, sample size, and the number of explanatory variables. In theory, the classification accuracy of QDA should be greater than LDA when the covariance matrices differ across the categories. In practice, the relative performance of QDA declines when the sample size is small and the number of explanatory variables is large relative to the sample.

2.4 Conditional Probability Approach

To avoid the shortcoming of the MDA method, some authors and researchers have recently used conditional probability models. Two such statistical methods, probit and logistic regression analysis, have the function providing conditional probability of an observation belonging to a certain class, given the values of the independent variables for that observation. Both of these methods use the cumulative probability function and neither requires that independent variables be multivariate normal nor that groups have equal covariance matrices with respect to the assumption of the linear MDA. Using the conditional probability approach thus essentially avoids all the limitations of MDA.

Like MDA these methods weight the independent variables to obtain a score for a given observation. Where they differ from MDA is that the weights are applied to maximise the joint probability of bankruptcy for the known failed firms and the probability of non-failed firms. They provide the conditional probability of an observation belonging to a category, given the values for the explanatory variables for the observation in question. They are generally solved using the maximum likelihood method. These techniques require less stringent assumptions and allow the independent variables can be discrete (Eg. binary) since normality is not required. This is useful for macro or industry dummy variables etc used in analysis. Also their significant and individual contribution can be assessed in some sense. Logit analysis has been increasingly used as a corporate failure prediction approach. Ohlson [1980] was among the first to use logit analysis in financial distress studies. Other users include Martin [1977], Mensah [1983], Gentry, Newbold, and Whitford [1985b], Casey and Bartczak [1985], and Zavgren [1985, 1988], Storey et al [1987], Peel [1987], and Keasey and McGuinness [1990].

Ohlson [1980] used the maximum likelihood estimation of the conditional logit model to predict corporate failure. A sample of 105 failed industrial firms was calculated from the balance sheet, income statement, funds statement, and auditors' report for three years of data prior to the date of bankruptcy and collected from the Wall Street Journal Index during the time period 1970 to 1976. Additionally, the failed firms must have been traded on the stock exchange or over-the-counter (OTC) during the three year period prior to the date of bankruptcy. Companies which did not report statements for the entire sample period were eliminated. Ohlson randomly selected the 2058 non-failed industrial firms derived from COMPUSTAT for one year prior to failure to construct the logistic function.

Seven financial ratios were selected to develop his model in the following listing:

1. size = log (total assets / GNP price level index),
2. total liability / total assets,
3. working capital / total assets,
4. current ratio,
5. net income / total assets,
6. funds from operations / total liabilities,
7. changes in net income.

Another two failure indicator variables were defined:

8. OENEG = one if total liabilities > total assets, 0 otherwise, and
9. INTWO = one if net income < 0, 0 otherwise.

These variables were selected on the basis of their popularity in the literature and perceived usefulness rather than from a theoretical basis or a dimension reduction technique to limit his variable list. Ohlson [1980, pp. 118] states that "no attempt was made to develop any 'new or exotic' ratios and no attempt was made to select predictors on the basis of rigourous theory". He noted that for bankrupt firms, 17 percent of the financial statements for the first year ended before a bankruptcy filing were not issued until after the filing. In such cases, to avoid confounding results, he substituted the statements for those of the previous fiscal period.

Three models were developed by Ohlson: models predicting failure within one year, within two years given no failure in the first year, and within one or two years were developed. All the variables in the model were significant at the 0.010 level except working capital / total assets and INTWO. The size ratio was significant at the 0.01 level in all three models. The likelihood ratio index (similar to R2 is multiple discriminant analysis) was 0.84, 0.80, and 0.72 for model 1, 2, 3, respectively. Classification errors were assessed using the same set of data from which the models were estimated rather than undertaking any hold-out tests. The classification accuracy for model 1, 2, 3, was 96%, 96%, and 93%, respectively. His test was made using a hold out sample because Ohlson felt that his sample was large and this would reduce bias. Ohlson concludes that account submission lags are important and be found they could be quite considerable for companies showing high probabilities of bankruptcy (up to 13 months).

Comment : Ohlson [1980] suffers from the lack of theoretical determination of his model. He uses a conditional logit model to classify failing and healthy firms. But he selects the independent variables without benefit of theory, assuring problems similar to those observed for discriminant analysis. For example, assets size is a variable with high significance in his model, but is also a scale factor in other ratios. This renders independent conclusions about asset size impossible to assess [Lev and Sunder, 1979, pp 190-3]. He also fails to use a matched sample technique, which would have controlled for implicit factors. In fact, Ohlson's model sustained error rates in the derivation sample of 12.4 percent of bankrupt firms and 17.5 percent of nonbankrupt firms. A hold-out sample was not employed.

Zavgren [1985] built a conditional probability failure prediction model which employs a dimension reduced data set, logistic analysis and an evaluation of the information content of the different functions for a five year period prior to failure.

She assessed the previous authors (Altman [1968], Deakin [1972], Blum [1974], Edmister [1972], Wilcox [1971,1973], Diamond [1976]) she found that they played loose with the assumptions of discriminant analysis. Results from MDA sometimes leads to inappropriate attempts to assess the meaning of individual coefficients. Hence, she believes that the logit method can avoid the criticism of the MDA method because it neither requires that independent variables be multivariate normal nor that groups have equal covariance matrices.

The sample selected in her study were drawn from those in the COMPUSTAT New York Exchange or Over-the-Counter and Research tapes. Forty-five failed firms were matched with forty-five non-failed firms on the basis of four digit industry code and asset size in the period 1972-78 for which data is available. 16 failed firms were matched with non-failed firms by the same procedure as used in the original estimation for hold-out sample during the period of 1979 to 1980. Zavgren employed the seven factors of two recent studies [Pinches, Mingo, and Caruthers 1973 and Pinches, Eubank, Mingo, and Caruthers 1975] and found them relatively stable over both short run and the long run, and developed a logit model by selecting at least one ratio from each factor with the highest factor loading.

One of the advantages of conditional probability models is that they allow interpretation of the significance of individual variable coefficients. She argues that the conditional probability model is superior to discriminant analysis because it yields a probability of failure rather than a dichotomous 0-1 prediction, and this probability may be employed by a user who may be capable of varying levels of response to risk of failure. Zavgren, in her model, asserted that the logit function provided significantly better probability estimates, and she found that the acid test variable was highly significant with a negative coefficient only in the first three years prior to failure for short-term prediction of failure, since an inadequate reserve of quick assets can bring about bankruptcy.

The profitability measure proved insignificant in any year. Financial leverage variable was significant for each of the five years. On the other hand, efficiency ratios such as the asset turnover, receivable turnover and inventory turnover were important indicators of financial distress for the longer-term (the fourth and fifth years) predictions because they measure the ability of the firm to use assets to full capacity and the concept that asset turnover measures efficiency in resource use. Receivable turnover and inventory turnover would both be expected to have positive signs for their coefficients; clearly when receivable turnover increase faster than inventory turnover or inventory turnover faster than sale turnover, failure looms.

She claims that her model compares favourably with other failure prediction models, the total mis-classification rates for the original sample were: 0.18, 0.17, 0.28, 0.27, and 0.20 for first year to fifth year prior respectively. The error rate for one year prior to failure was similar to Ohlson's [1980] and significantly lower than that reported by Altman. Mis-classification rate for the hold-out sample was 31 per cent for years one through five, respectively.

One important aspect of the Zavgren study is that she looks at the information content of the different year prior models by using information theoretic measures. She found the amount of information increases over the five year period to failure by an average 18 per cent for the failed firms and 16 per cent for non-failed firms. However, it needs to be noted that the sample selection procedure included only companies which had complete and up-to-date information.

Zavgren's [1985] study is especially interesting because it provides economic interpretations and may indicate the future area in bankruptcy prediction research.

Comment:

1. There are advantages in using a logistic regression model rather than a linear discriminant model because it is relatively robust, i.e., many types of discriminant analysis's underlying assumptions do not lead to logistic formulation. The linear discriminant analysis approach, by contrast, is strictly applicable only under the assumption that underlying variables are jointly normal and the two groups have equal covariance matrices. Logit and probit methods are not restricted by these assumptions.

2. Another advantage of logistic modelling relates to its use as an alternative to contingency table analysis. Gordon [1981] points out that logistic regression models have played a major role in biological and medical applications where cross-classified tables with large numbers of cells are typically replaced by a logistic regression among the variables.

However, it is somewhat doubtful whether the calibration of any such model could be verified in view of the sparseness of company failure.

2.5 Classification Trees and Nonparametric Approaches

Discriminant analysis (DA) and conditional probability models (e.g. Logit or Probit) have been the most widely used methods for predicting company failure, as well as for other classification problems in finance and accounting. However, studies by Joy and Tollefson [1975], Eisenbeis[1977], Altman and Eisenbeis [1978], Ohlson [1980], and Zavgren [1985] comment on and/or criticize possible misapplication and potential misinterpretation of discriminant analysis in the identification of bankruptcy. The Recursive Partitioning Algorithm [RPA] and the Non-Parametric Approach [NA] appear to overcome some of the shortcomings and problems of traditional DA as well as other conditional probability methods.

RPA is a computerized, iterative, non-parametric classification technique, based on Frydman [1977], Gordon and Olshen [1978], and Breiman et al 's [1984] pattern recognition, that estimates a classification rule as a sequence of binary partitions of the independent variables. At each step, the method divides a sub-sample into two groups by partitioning and selecting the independent variable that most improves the homogeneity of category tasks applied respectively to the two outcoming groups. This approach appears to overcome some of the shortcomings and problems of traditional DA as well as other parametric techniques (e.g. the zero-one linear probability model). The number of misclassification errors identified as well as the expected costs of misclassification are often smaller than those obtained with DA, the logit and probit analyses. It has attributes of the classical univariate approach to classification and multivariate procedures. RPA works in a forward stepwise procedure to select the independent variables that will classify failed and non-failed firms with the lowest mis-classification cost. An appropriate cut-off is established. Barniv and Raveh [1989] described some properties of the non-parametric procedure are as follows:

1. The RPA classification rule partitions the variables space into a number of rectangular regions until the process stops when the terminal nodes appear. The two group DA classification rule, on the other hand, partitions the variable space into only two half-plane regions.

2. No assumption of specific parametric distributions is required. Hence, qualitative (categorical) variables, as well as quantitative variables, can be treated.

3. Neither symmetric distribution nor equality of dispersion is required in order to employ linear discriminant functions. Smaller number of variables and equal group sizes seem to lead to less biased results. RPA or NA is unaffected by violation of the equality of group covariance matrices. If the missing data

must be used to classify an object into one of several categories, RPA or NA can then cope with the missing information since the splitting point is not influenced by outliers (missing data).

4. The method will seek to minimize mis-classification costs and treat various costs of mis-classification.

5. The method is optimal for non-overlapping distributions of scores obtained from the two groups.

6. In the case of K > 2 ordered groups the procedure can be generalized in a straightforward manner.

7. A classification matrix is easily obtained, and costs of mis-classification could be calculated.

Frydman, Altman, and Kao [FAK, 1985] employed a sample of 58 failed industrial companies and randomly selected 142 non-failed manufacturing and retailing companies during the period 1971 to 1981. They used 20 financial variables which had been found significant in predicting business failure as their variable set and fixed prior probability for bankrupt and non-bankrupt companies of 0.02 and 0.98, as well as a variety of mis-classification cost estimates ranging from 1 to 70. For each mis-classification cost ranging from 1 to 70, they compared the performance of stepwise DA to RPA based on two classification trees. They found that RPA retains the joint positive attributes of multivariate information content and univariate simplicity. Since this methodology is non-parametric, neither symmetric distributions nor equal variance-covariances are required. The classification accuracy of RPA is superior to the DA in most initial and hold-out sample comparisons.

Comment:

Unfortunately, this technique does not provide an estimate the probabilities of group membership or a means of evaluating significance of variables. Because a variable may enter more than once at different stages of the partitioning process, it is not clear how to assess the importance of discriminators. Next, model over-fitting is also a problem. Frydman, Altman, and Kao [1985] point out that it is difficult to ascertain the relative importance of variables. One might suspect that the first variable selected by the method is most important. However, the procedure is a forward selection technique that entered in the process based on the forward stepwise selection technique that does not review the previous selection processes in light of recent ones. It is enlightening to examine the univariate contribution, and once a variable is selected as the first splitting variable, the tree is constrained to include that measure first, the same variable may reappear twice as the partitioning process confuses the interpretations of importance of variables. Multivariate Analysis (DA) models are estimated by maximizing the ratios of between group to within group variance, and then assign observations into the specified groups on the basis of specific error costs and prior probabilities. On the other hand, RPA technique does not provide estimate of the probability of group membership. "Changing the costs and priors might very well vary the variable selected for splitting"; hence, RPA models appear to be more sensitive to costs and priors than DA models [Frydman, Altman, and Kao 1985].

2.6 Survival Analysis

Keasey and Watson [1990] suggested this technique which assumes that the failure event should be time independent. Survival analysis should be thought of as an essentially univariate technique - the variable of interest being the length of time a company has survived. This length of survival variable can then be regressed on a number of independent variables using traditional regression techniques. An introduction to this technique is provided by Cox and Oates [1984].

2.7 Summary and Conclusion:

This chapter reviewed the previous studies employing a variety of failure prediction approaches which have been published to date. These studies were divided into four broad groups. The first part reviewed the studies which introduced the pioneer authors using accounting information in failure prediction included Winakor and Smith [1935], Fitzpatrick [1931,32], Merwin [1942], Tamari [1966], and Beaver [1966] studies. The second and third parts reviewed the multivariate discriminant analysis and conditional probability analysis, and the fourth part reviewed the non-parametric, recursive partition analysis, and other specific approaches. The following is a summary of the above reviewed studies

1. Failure prediction studies have followed a trend that started with univariate analysis, proceeded to discriminant analysis, and increasingly uses logit or probit analysis, and lately, the recursive partitioning or non-parametric approach. Usually the variety of failure prediction statistical techniques have been used in order to either build a more meaningful analysis or enhance a better predictive ability in terms of their distinguishing financial characteristics (their financial ratios, independent variables in the each methods). Nevertheless, most previous studies of corporate failure prediction models have been somewhat disappointing, because they have not carefully examined the data stability problems due to changes in inflation, time, and the nature of business cycles. These factors may have influenced the classification accuracy of the results.

2. Keasey and Watson [1991, p. 92] commented that the various statistical techniques are able only to optimally weigh the information provided. The applicability of the resulting predictive functions will be crucially dependent upon the assumptions made regarding the costs of misclassification and the structure and availability of the data.

3. The stability of the financial ratios reviewed in the above studies have not been investigated in most previous failure prediction models. The availability of empirical evidence has shown that some accounting ratios may measure different financial attributes for different periods of time and for different sectors of companies. Therefore, a failure prediction model should develop a technique to control industry variation within heterogeneous sector conditions in order to avoid unstable financial ratios. The use of industry relative ratios, created by dividing a firm's ratio by the industry's average ratio, in this study will be introduced to alleviate the data instability problem.

4. Most of the previous studies were not exactly concerned with how the different macro-economic environments can be expected to have an impact on the stationarity of failure prediction models. A reason for suspecting instability is that the characteristics of external economic environments which might be expected to affect the financial condition of firms change over time. In order to cope with these instability problems, in this study, according to the degree of movement of the business cycle period, the sample is divided into three homogeneous sub-periods based on the interest rates, inflation rates, and real GNP indices in this period from 1974 to 1985 [see Table 6-18]..

In theory, Platt and Platt [1990] say that the stability of the ex-post to ex-ante classification results are similar to those reported by single industry studies of commercial banks. Focusing on one industry is analogous to using industry relative ratios in samples including several industries since the relative position of firms within the industry is reflected by the relative position on any given financial ratios [p. 46]. None of the previous studies has examined the stability of forecasting from ex-post sample to an ex-ante sample between one single industry and adjusted ratios (using industry relative ratios). In this study, we will examine the results. In the next chapter, we discuss some methodology problems regarding the selecting independent variables.

Chapter 3 : Methodology For Choosing Independent Variables and Dependable Variables

3.1 Developing A Theory of Failure Prediction

Not too many theories have been developed for the prediction of corporate failure. Little serious consideration has been given to the interests and motivations of the agents involved in the failure process due to lack of comprehensive theoretical development. Generally, model's development has been data driven rather than theory led. Generally, little serious consideration has been given to the interests and motivations of the agents involved in the failure process [Keasey and Watson, 1990b]. In terms of developing a theory of failure prediction, four categories can be discussed as follows: (1). theory as a stimulus, (2). factors affecting survival of business, (3). stages of business failure, and (4). theoretical mathematical models.

3.1.1 Theory as a Stimulus

Ideally, Jones [1987] states, the researcher will draw on an economic theory in selecting those variables that will predict bankruptcy. A major criticism of many previous studies is the limited attempt made to develop any theoretical foundation in failure prediction that would identify the variables to be incorporated in the discriminant function. Cash flow models have been focused on failure prediction as a theory stimulus. In his pioneering work, Beaver [1966, p. 80] derived from his cash flow model four postulates concerning failure:

1. The larger the reservoir of liquid assets, the smaller the probability of failure.

2. The larger the net liquid assets flow from the operation, the smaller the probability of failure.

3. The larger the fund flow expenditures for operations, the greater the probability of failure.

4. The larger the amount of debt held, the greater the probability of failure.

But his selection of variables was not limited to his four postulates and included financial ratios on the basis of popularity and performance in other studies in order that he might provide generalized results as to what financial ratios are liable to be consistent predictors in failure prediction.

Lev [1974] commented on this issue as follows:

> "There is no well-defined corporate failure theory. Lacking such a fundamental theory, researchers employ a trial and error process of experimenting and a large number of measures to test it. Such as univariate and multivariate and non-parametric statistical techniques."

Ball and Foster [1982] have observed that sophisticated models of failure prediction quoted in the literature generally come from the statistical or mathematics literature, which are of little assistance in selecting predictor variables. They have reviewed hundreds of empirical studies which classified the corporate financial reporting literature into four topic areas: (a) corporate disclosure , (b) accounting method choice, (c) time-series analysis, and (d) financial distress analysis. They find, in the literature reviewed, that a frequent observation throughout is that a limited role is played by theory in explicitly guiding empirical research projects in corporate financial reporting. Statistical and mathematical models have not yet been able to express the richness of the institutional environment in which financial statements are produced or used. They concluded that "empiricists who require their research to be explicitly guided by theories that relate to the institutional environment generating the data being examined would probably seek out research areas other than those examined in previous literature. Empiricists working in the areas examined have to be able to accept a relatively high degree of uncertainty in important research choices including the variables to examine, quasi-experimental design to use, and the inferences that can be drawn." As noted earlier, advances of theoretical reasoning play an important role for in failure prediction.

Unfortunately, Jones [1987, p. 135] quoted that most researchers after Altman [1968] have not yet applied theoretical models to empirical research, and have jumped straight into a sophisticated statistical or mathematical analysis, and have not considered economic guide-lines to assist in selecting independent variable. A number of authors, for example, Beaver [1966], Deakin [1972], Blum [1974], Mensah [1983], Casey and Bartczak [1984], and Gentry, etc [1985a], have recommended the ratio cash flow / total debt to be useful in developing failure prediction theoretical models. However it appears that to date they have failed to prove cash flow value in empirical study especially defined it on the basis of their own subjective notion, respectively. To some extent, these studies intend not only to improve prediction accuracy but also to respond to popular assertions that cash flow information is especially useful in evaluating sovlency. The lack of theoretical foundation is not uncommon in accounting empirical studies. Of course, a more developed model tends to be highly illustrative and require strong assumptions regarding the soundness, computational abilities of economic agents and the efficiency of the capital markets. However, without identifying the external or internal economic environment of company bankruptcy, it will be more difficult to determine the appropriate model from one period of data to another period of data based on various external economic cycle factors. More understanding of the process whereby firms become bankrupt, rather than merely predicting it, must be considered jointly with external economic cycle. Jones [1987] concluded that

'Ideally, theory would suggest a casual link between selected variables and financial distress; the proposed linkage could then be tested by an appropriated constructed predictive model. Unfortunately,, the lack of theory has prevented the comprehensive use of this scientific approach".

3.1.2. Factors Affecting Survival of Business

While businesses fail for a wide variety of reasons related to both internal and external factors, most analytical research done on failing firms uses ratio analysis as its foundation. In contrast, Argenti [1976] produced a dynamic model of business failure which is less dependent on traditional financial ratios than on the operating elements of the enterprise and its management foundation. The descriptive factors affecting survival of business summarized by Argenti [1976], identifies the causes and symptoms of corporate failure to be:

(A) Internal Factors:

I. Bad management manifested through,

a. Lack of responsiveness to change in technology
b. Bad communications
c. Misfeasance and fraud
d. Insufficient consideration of cost factors (research and development costs in particular)
e. Poor knowledge of financial matters
f. High leverage position-particularly harmful in an economic downturn

Bad management is the root reason for the failure of a firm. Dambolena and Khoury [1980] have categorised it on the foundations of Argenti's model in the 6 ways described above. The major element in bad management in an organisation identified by Argenti was the 'autocrat" or "one man band" in which a dictator dominates the top management and rarely heeds the advice from his colleagues working within the enterprise. In this environment, most businesses were born to die due to lack of a good leader from the outset. Some common types of bad management occur when a firm expands faster than it should. For example, if the expansion is not carried out effectively, or if the company does not have access to adequate amounts of capital, it can easily cause a firm to deteriorate. The deterioration may come in the form of increased bad debts, increased production costs, or inability of management to control a larger organization. Argenti's view is that companies do not fail suddenly, but with clear symptoms of impending disaster. Many of these symptoms are bad management oriented and not financial ratios only. Argenti argued that financial ratios, because they were merely **symptoms** of business failure, are unable to yield significant insights into the underlying processes or **causes** of corporate collapse. Therfore, he recognised that financial ratios are open to various forms of manipulation and were therefore likely to become less reliable as failure approaches. Ross and Kami [1973] report that companies fail because of bad management. Altman [1983] also states that the overwhelming reason of individual firm failure is managerial incompetence. Many writers mentioned above have examined the internal factors affecting survival of business which are attributable to and controllable by management.

(B) External Factors:

I. Labour Unions: Too high a wage settlement causing the firm to pay its employees in excess of their marginal product.

II. Government Regulations which impede, in some instances, the functioning of the market system distorting in the process its signals to the corporate decision makers.

III. Natural Causes: natural disasters, demographic changes, etc.

Towlson [1977] also found that failure of companies arose from external factors including : (1) industry and economic trends; (2) economic and financial conditions; (3) technical obsolescence; (4) government policy. Therefore, external non-financial and non-quantifiable factors that affect the survival of business are those beyond their direct control. This study examines the link between measures of U.K. business failures and external factors related to the business cycle.

3.1.3 Stages of Business Failure From the Financial Viewpoint

Previous studies attempt to develop early warning systems that can be widely classified into two categories; first, there are those that are essentially a list of the causes and symptoms that failing companies are said to display, and second, those that select failing companies by financial data calculations. Foster [1978] states that there is a consecutive series of events that can lead up to liquidation: (1) Sales decline in major products, (2). Deferment of payments to short-term creditors, (3) Omission of preferred dividends, (4) Default on bond, (5). Filing of bankruptcy. This definition of his failure is consistent with Beaver's [1966]. In Richmond's paper, "Possible Future Insolvencies: Danger Signs and Avoidance", (1977). Indicators of possible future insolvencies as well as present insolvencies can be allocated to the three stages: management, trading, and accounting. Accordingly, the following list was separated by A. J. Richmond into three stages (see Table 3.1).

These stages of failure show the firm's position and nature of items in each of the three broad areas of lines. Previous theoretical models (for example, Beaver [1966], Mensah [1983], etc) did provide a justification for the usefulness of financial ratios as financial failure predictors. However, they lacked a theoretical foundation to specify which ratio was to be included in their research. A lot of time and effort was devoted to determine the different combinations of financial ratios, testing their discriminatory and predictive abilities by factor analysis and stepwise regression, and constructing the relevant multivariate discriminating models.

Table 3.1 Stages of Business Failure

A. Management

1. Board Composition and balance
2. Collective responsibility of the board
3. Chain of responsibility and middle management

B. Trading

1. Overtrading
2. Competitive quoting / erosion of margins
3. Outsize project
4. High gearing
5. Resistance to change / technological advances
6. Unwitting changes in the fundamental activity of the business
7. Short-term borrowing for longer-term assets
8. Deterioration of service

C. Accounting

1. Inadequate / erroneous out-of-date accounts
2. Lack of cash flow budgets
3. Unsystematic payment of creditors and collection of debtors
4. Creative accounting and 'beneficial adjustments'.

Source: A.J. Richmond [1977]

3.1.4 Developing a Theoretical Mathematical Model

The gambler's ruin model proposed by Wilcox [1971 and 1973] is a statistical model that assumes a gambler has an amount of money that will either grow or to be deleted to zero by a series of independent trials. Wilcox views the firm as being equivalent to a gambler that becomes bankrupt when its worth falls to zero. Wilcox's model was based on a Markov process and the probabilities of a firm's failure. He expanded his initial theoretical model to be more realistic by incorporating barriers to entry of new capital and management. He assumed that a firm has a given amount of capital and that changes in that capital were random.

Wilcox observed 52 failed firms from 1949 to 1971 and employed Beaver's paired-sample design to make his analysis. He found that his own model's predictive ability was slightly higher than Beaver's but statistically insignificant. The attempts made to apply this model have been disappointing, perhaps due to the fact that the theory he used was too simple, since it assumed that cash flow results from a series of independent trials, without the benefits of any intervening management action. Whereas his theory specified a functional form for the probability of ultimate ruin, Wilcox found that this probability was not empirically meaningful. Although the theory provided a functional form for the probability of ultimate failure, he found that most of his sample's data violated the theory's assumptions and suggested additional hypotheses which would lead to improved failure predictors.

Faced with this problem, Wilcox [1976] removed the functional form suggested by the theory but used its variables to construct his own prediction model. He found that the gambler's ruin model represented a straightforward conceptual framework from which fundamental risk parameters could be derived. The basic variables used in the gambler's ruin model were net liquidation value and the processes which caused it to change.

Wilcox adapted the classic gambler's failure problem to measuring business risk and focused on Net Liquidation Value (NLV) and the factors that cause it to fluctuate. NLV is, in the language of systems dynamics, simply a dollar level determined by liquidity inflow and outflow rates. The inflow rate in a given period was defined as net income less dividends. It was governed by a firm's profitability and management's dividend policy. While the outflow rate represented the increase each period in the book value of assets less the increase in the liquidation value of those assets. The rate is determined by capital-budgeting decisions and current-asset controls. He assumes a gambler has an amount of money that will either grow or be depleted to zero by a series of independent trials. The company is considered as the gambler by Wilcox.

When the inflow rate [gain] exceeds the outflow [loss] rate, NLV increases; when the opposite occurs, NLV decreases. When the flows are equal, the level remains constant. Using the empirical test results, Wilcox [1976] compared it with Beaver and Altman's classification tests.

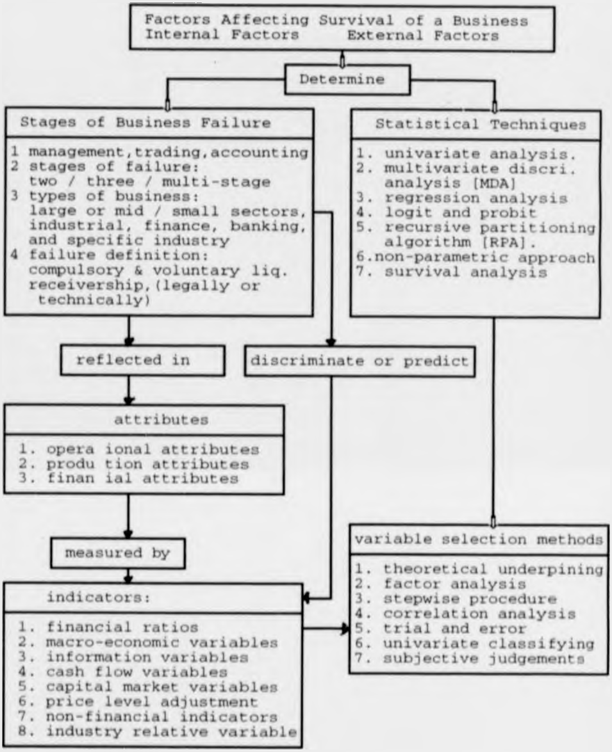
Wilcox [1976] contented that his gambler's ruin approach compared "very favorably" with Beaver's and Altman's models, especially since (1) his model did not represent the result of statistical searching; (2) his model was tested over a long period of time, during which inflation had altered typical financial ratios; and (3) his model was derived from a conceptual framework with implications for the managerial process.

3.1.5 A Comprehensive Theoretical Model

As a conceptual framework for business failure prediction, the following Table 3-2 integrates the above theories and introduces the various stages of business failure. Failure/non-failure and ratios/non-ratios type indicators are treated both as a dependent/criterion variable and a set of independent/predictor variables respectively in the discriminant model. Once the discriminating model, based on dichotomous grouped data developed by a statistical technique, is established, a new observation could be classified as a failed or non-failed firm by this model and then the classification accuracy of dichotomous groups could be predicted. Most of the previous studies have constructed their prediction models based mainly on this framework but with some degree of variation. These can be categorized as (1) the use of statistical discriminating and classification techniques, (2), the differences in research objectives and subjects, and (3) the selection of significant predictor variables. These variations have been incorporated into this conceptual framework in order to build a comprehensive model for financial failure prediction.

It should be noted that differences do actually exist between research topics and objectives. Since different operational definitions of failure have been made, it is obvious that different sampling designs must also be formulated. Foster [1978, 461-3] has noted that the term financial distress is so ambiguous that different researchers have used different criteria to define it. Especially in the not-for-profit sector of the economy it is a difficulty task. In the selection of variables, most previous studies have used different methods to determine which ratio or which combination of ratios should be included in the appropriate model, even if a variety of variables have lacked well-accepted theoretical underpinning. An examination of the previous empirical studies indicated that Wilcox [1971,1973, and 1976], Blum [1974], Argenti [1976], Ball and Foster[1982], etc have developed theoretical models to select the more meaningful variables. But Scott [1981] and Altman [1983] conclude that for all of these studies, results are difficult to assess.

Table 3-2 A Comprehensive Model For Financial Failure Prediction



Source : This study.

3.2 Selecting Financial Ratios

3.2.1 Choosing Important Financial Ratios

Financial ratios derived from financial statements are used extensively by both practitioners and researchers. Practitioners are generally concerned with the evaluation of corporate performance through various financial ratio analysis methods, such as the study of the time-series of ratios and the comparison of a given firm's ratio with industry standards. Researchers in accounting, finance, and economics use financial ratios in the examination of various issues, such as the relationship between financial data and common stock characteristics [Lev & Sunder, 1979]. However, in the failure prediction context, there are two principal reasons for using financial ratios They are:

1. To allow for the effect of the size of failed and non-failed firms on the financial variables being examined. Lev and Sunder [1979] said that use of ratios was "necessarily based on a hypothesis (either explicitly or implicitly assumed) about the relationship between the numerator variable (e.g., sales) and the denominator size variable (e.g., Working capital)." Control for size by ratios was only satisfactory in certain restricted conditions. Mcleay and Fieldsend [1987] concluded that ratio remained tenable allowing for size and sector effects identified by Lee [1985] and Buijink and Jegers [1986]. However, there are other studies with opposite results, such as McDonald & Morris [1985, 1986].

2. To allow for industry-wide factors. Ratios aid comparisons between a subject firm and its industry In practice, ratio analysis of a single homogeneous industry's ratios will be compared with aggregate industry norms which may be location measures, such as the industry mean and median ratios, and inferences about the single industry performance are based on the difference

between the single industry's ratios and the aggregate industry norm. In empirical research, control for size effects is done by dividing the firm's ratio by industry average ratios [Lev and Sunder, 1979]. While location measures may be unified in normal distribution, they will not in the case of skewed distributions, rendering the choice of location variable problematic. [Barnes, 1987, p. 451].

Financial attributes can be measured through the use of financial ratios - where each ratio expresses a relationship between two accounting items or an aggregate of items that are contained in published financial statements. In many of the previous studies, financial ratios were selected by the following criteria:

1. Occurring often in the literature. The most popular ratios advocated in the literature are perceived by many to reflect the critical relationships.

2. Efficiency and good performance in previous literature or related studies;

3. Dependence upon a "cash-flow" concept; and

4. Consultation with financial analysts and practitioners.

The presence of any one of the criteria was a satisfactory requirement for inclusion in this study. In every instance, this study limited itself to testing existing ratios rather than to developing new ones (see Beaver 1966, Horrigan 1966, and Taffler 1977).

Cash flow framework has been used as a theoretical basis by Beaver [1966], Blum [1974], and Lau [1982]. Beaver classified a total of thirty ratios into the six groups: cash flow ratios, net income ratios, debt to total-asset ratios, liquid-assets to total-asset ratios, liquid-asset to current debt ratios, and turnover ratios. The ratio with the best classification and with the lowest percentage of classification error over the five year period was then chosen from each of these six groups. Using the financial ratio, cash flow to total debt, and a properly cut-off score, Beaver was able to classify accurately 87 per cent of the firms in his hold-out sample one year before bankruptcy and correctly classified 78 per cent five years before bankruptcy. Other accurate indicators included net income / total assets, total debt / total assets, working capital / total assets and current ratio. Beaver's..et al [1968a] study can be regarded as a supplement of his 1966 study. He employed the same data and methods to test the hypothesis that liquidity ratios were better than non-liquidity ratios in predicting bankruptcy. Beaver's [1968b] third study included the analysis of the change in stock prices of bankrupt firms. Both studies are consistent with the results of Beaver's [1966] findings. Accordingly, he suggested that investors appear to use financial ratios in their investment decisions and that the stock market appears to anticipate the apparent future bankruptcy in the price of a given company's stock.

Altman [1968] used a multiple discriminant analysis (MDA) technique with earnings before interest & tax to total assets, working capital to total assets, retained earnings to total assets, equity at market value to book value of total debt and sales to total assets as independent variables. In contrast to Beaver's study, the accuracy of Altman's predictions declined as the time span prior to bankruptcy. In his sample, the model proved to be extremely accurate in predicting bankruptcy, with 94 percent of the initial sample and 95 percent of overall firms in the bankrupt and non-bankrupt groups. The model's predictive accuracy decreased for the second year preceding to bankruptcy with an overall accuracy rate of 72 percent. Altman concluded that as a firm nears bankruptcy, all ratios tend to deteriorate. Altman [1970, reply] was convinced that Ratio analysis is an important tool for the financial manager and it has demonstrated an impressive ability to predict corporate bankruptcy by analyzing the characteristics of different groups of firms.

There are many appropriate ratios reported in the literature. Understanding is needed to ascertain a limited set of financial ratios. Naturally, different researchers often included different ratios. Hamer [1983] examined four variable sets : those selected by Altman [1968], Deakin [1972], Blum [1974], and Ohlson [1980] to see whether the classification accuracy was sensitive to financial ratios selection or not, using a sample of 44 failed and 44 matched non-failed firms. She tested four alternative variable sets on firms which failed from 1966-1975. For each of four variable sets, a linear discriminant model, a quadratic discriminant model, and a logit model were examined.

Nevertheless, each set included variables that measure the first three conventional categories: profitability, liquidity, and leverage, which are commonly used in discussions of financial statement analysis [Lev, 1974, Foster, 1978]. The classification accuracy of each possible pair of the four sets was compared using a chi-square test and examined for each year prior to failure. She demonstrated empirically that there were no significant differences in classification results achieved by using four different variables sets drawn from well-known prior studies, regardless of whether the logit or linear discriminant technique was used. She found that all four variable sets predicted bankruptcy with comparable accuracy. Eventually , results on the usefulness of specific ratios vary. She suggested that: the ability of models to predict failure is not particularly sensitive to the specific set of ratios used, nor to the choice of linear discriminant analysis as opposed to logit analysis. Since predictive accuracy does not appear to be affected by these choices, the analyst should consider a variable set which minimize the cost of data collection [p. 304]. In this study, selection of independent variables is discussed in sub-section 5.1.2.3.

3.2.2. Categorizing of Financial Ratios and Reducing the Variable Set

Overlaps among financial variables can still be found in most of the recent studies. Eliminating such overlapping problem would aid the development of a useful set of financial ratios. Due to the lack of theoretical guidance, many previous studies in developing empirical failure prediction models have been forced to employ some statistical methods to cope with a multitude of variables. Accordingly, a statistical tool designed to summarize such inter-relationships is factor or principal component analysis. One of the functions performed by factor analysis is to group variables into a few factors that retain a maximum of information contained in the original variable set. Factor analysis is used when the research is concerned with discovering which variables in the data set form coherent subgroups that are relatively independent of one another.(A further explanation of factor analysis is given later in section 5.2.5.1). A researcher may leave out ratios that were not independent. Jones [1987] observed that using too many ratios can actually make a model less useful.

Zavgren [1983] points out that there is an implicit assumption that ratios that have a specified relation with the dependent variable in the sample set will have the same relation in the prediction set. A model that uses too many ratios may be over-fitted, so that it is highly successful in the classification of the sample data set, but less effective in application. In additional, a model with a lot of variables is likely to have significant multicollinearity and be difficult to interpret.

Foster [1978, p. 28] states that the most widely employed cross-sectional tool is financial ratio analysis. Four traditional categories and ratios within each category are commonly used to reflect the general financial characteristics of firms : (1). liquidity ratios, (2). leverage / capital structure ratios, (3). profitability ratios, and (4). turnover ratios. A study by Pinches, et al. [1973 hereafter, PMC] criticized the traditional classification schemes of financial ratios as ad hoc and ignoring the empirical relationships existing among financial ratios. They then attempt to develop an empirically-based classification of financial ratios. Using factor analysis to determine the long term stability / change patterns during 1951-1969 in financial ratio patterns in the USA and to reduce a set of variables into a small set of derived factors. These factor patterns have the property of retaining the maximum amount of information contained in the original data set. Financial ratios were grouped with each of seven factors among 40 financial ratios for a sample of 221 industrial firms. These seven patterns occurred in each year examined, accounting for a consistently high amount of the variance contained in the original data matrix. The classifications remained relatively stable over the 19-year period studies. A subsequent study by Pinches, Eubank, Mingo, and Caruthers [1975 hereafter, PEMC] showed the short-term stability of these factors. They also demonstrated that a hierarchical classification of empirical financial ratios can be constructed. According to their findings, financial ratios can be represented by seven factors:

1. Return on investment,
2. Financial leverage,
3. Capital turnover,
4. Short-term liquidity,
5. Cash position,
6. Inventory turnover, and
7. Receivables turnover,

These groups were reasonably stable over time. Three separate factor patterns of differences, such as cash position, inventory turnover, receivables turnover, were separately grouped from traditional classification. The above seven factors were reduced from 48 to 7 variables (an 85% reduction) and still accounted for 92% of the variation in the initial data matrix. The results of theses analysis are summarized in Table 3-3

Table 3-3 Data Reduction in Factor-Analyzed Financial Ratio Space

Study	Variable	Factor Space	% Reduction Space	% Variation Explained
Pinches and Mingo [1973]	35	7	80	63
Pinches, Mingo, and Caruthers [1973]	48	7	85	91,92,87,92
Stevens [1973]	20	6	70	82
Libby [1975]	14	5	64	Not Reported
Pinches, Eubank, Mingo, and Caruthers [1975]	48	7	85	92

Source from: Chen and Shimerda [1981], p. 53

Pinches and Mingo reduced their data set for bond ratings from 35 to 7 variable (an 80% reduction) and still accounted for 63% of the variation in the original data matrix. Stevens [1973] reduced 20 variables to 6 (a 70% reduction) and accounted for 82% of the total variance. Libby [1975] reduced his 14-ratios set to 5 ratios (a 64% reduction) with very little loss in the prediction ability of the model. PEMC [1975] reduced their data set from 48 to 7 variables (an 85% reduction) and still accounted for 92% of the variation in the initial data matrix. PEMC [1975] also demonstrated that a hierarchical classification of empirical financial ratios can be constructed. Building on this, the extent of cross-sectional stability of ratio classification has been examined by Johnson [1979]. He compared the financial ratio patterns for retail and manufacturing firms in the years of 1972 and 1974. He reported that a high degree of stability in terms of the consistency of factor loadings across the two industrial groups. Johnson also confirmed that decomposition measures obtained through use of information theory method provided another dimension of financial information not captured by the usual financial ratios.

Elsewhere, Laurent [1979] used Principal Component Analysis [PCA] to derive a set of ten financial ratios which explained 80 per cent of the variance in an overall set of forty-five financial ratios in his study of Hong- Kong companies. He found that only a few selected ratios and relatively independent ones have to be used instead of a much larger set;

Gombola and Ketz [1983] found that cash flow measures also represented a separate dimension of firm performance, although general price-level adjusted and specific price level adjustment financial ratios did not [Mensah, 1983]. Gombola and Ketz [1983] followed on the work of Pinches, Mingo and Caruthers [PMC, 1973]. The aim of their study was to examine the impact of cash-flow measurement upon the classification patterns of financial ratios. They performed a factor analysis on a set of 40 variables calculated on an historical cost basis and a general price level basis, using data on 119 manufacturing companies over a 19 year period. Then for each year, factor analysis was applied to the 40 financial ratios. They derived eight factors (those with eigenvalues >1.0), seven of which were substantially similar to the seven factors in the Pinches, Mingo, and Caruthers study, and the ratio with highest correlation with each factor during the typical year studies include:

(1) Cash position (CP) : cash / current debt,
(2) Cash flow from operations (CFFO): cash flow / total assets,
(3) Debt structure (DEBT) : total debt / total assets,
(4) Short-term liquidity (STL) : quick assets / current debt,
(5) Return on investment (ROI) : income / equity,
(6) Inventory intensiveness (INV) : cost of goods sold / inventory,
(7) Receivable intensiveness (REC) : receivables / inventory,
(8) Capital intensiveness (CI) : current assets / total assets.

They found that cash flow and cash position ratios have different correlation structures compared with the ratios usually grouped under the liquidity category and the more careful calculation of cash flow data increased the importance of the information. Turnover ratio category is a relatively heterogeneous one. Nevertheless, the analysis of classification patterns for financial ratios will provide assistance in selecting potentially useful variables in decision models or behavioural analyses.

Ezzamel, et al [1987] selected samples from the EXSTAT data in 1971-1982 and included a large number of UK and overseas companies. Both orthogonal and rotations have been used in their studies. The ten financial patterns for UK manufacturing companies reflect five broad categories of a firms's financial position: (1) total funds, (2) profitability, (3) working capital, (4) short-term and long-term liquidity, and (5) asset turnover. The financial ratios most highly correlated with each factor. Thus, in their conclusion, few carefully selected ratios can be used to represent the main financial patterns with relatively little loss in information.

Chen and Shimerda [1981] presented a table contains 31 financial ratios that have been found to be useful in predicting financial distress. Using factor analysis, they found that the five studies they reviewed had similar factors to the seven obtained by Pinches, Mingo, and Caruthers [1973]: Return on Investment, Capital Turnover, Financial Leverage, Short-Term Liquidity, Cash Position, Inventory Turnover, and Receivables Turnover. They point out that it would be better to select only the highest absolute factor loading ratio from each factor when developing further analysis and also found a variety of factor analyses seemed to parallel the results of Pinches and his colleagues. Many of the ratios included in the studies are highly correlated with one another.

3.2.3 The Use of Financial Ratios For Predictive Purposes

Financial ratios are almost always used for predictive purposes, (either implicitly or explicitly), as indicators of a firm's financial and business performance and its characteristics [Barnes, 1987]. The predictive ability of financial ratios has been indicated a good explanation in many kinds of business and economic events. Notable first pioneer work includes Beaver's [1966] univariate analysis and Altman's [1968] multivariate analysis. Each of the financial ratios in Beaver's study was analysed and the cut-off point selected in order to maximise the number of accurate classifications for a particular sample. Altman used the well known multivariate discriminant analysis for credit, investment and going-concern evaluation. Financial ratios have been used in identifying the financial characteristics of problem banks, [Sinkey, 1975; and Pettway and Sinkey, 1980] as well as the lending decisions and capital adequacy aspects [Dince and Fortson, 1972].

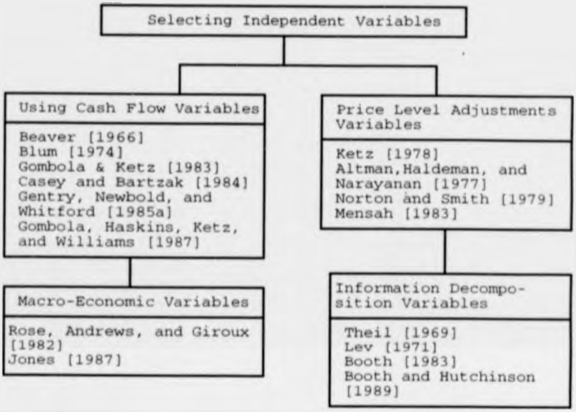
Different kinds of industries provide different types of ratios as a norm to demonstrate the causes of bankruptcy for failed and non-failed firms. It is necessary to establish that certain ratios values imply failure or non-failure, which requires a model to link given ratio values to those two groups, [Johnson, 1971]. Although financial ratios have been developed in failure prediction for a few decades, there are no certain ratios that consistently show up in the different previous studies. Dev [1974] and Chen and Shimerda [1981] have analysed the main studies and tabulated the frequency of the individual ratios and the main factors included. They suggest that how financial ratios are selected needs to be considered. Which are the useful ratios for failure prediction and which are the significant ones ? The published studies show that ratios are usually selected on the basis of their popularity in the literature together with a few initiated by the researcher [Barnes, 1987].

Financial ratios also have been used to assess and forecast company risk. For example, Falk and Heintz [1975] used a partial order scalogram technique (industry financial ratio) to scale industries according to their degree of risk. Gupta and Huefner [1972] used cluster analysis to relate ratios to established economic characteristics of the industries concerned. For the forecast company risk, Thompson [1976] measured the stock market systematic risk using the financial ratios. O'Connor [1973] investigated the statistical relationship between financial ratios and rates of return on common stocks. He concluded that financial ratios are useful in forecasting future rates of return.

3.3 Selecting Independent Variables

In this sub-chapter, we summarize the studies discussed in the following Table 3-4

Table 3-4 A Summary of Selecting Independent Variables



Source: This Study

3.3.1 Using Cash Flow As An Independent Variable

Beaver [1966] selected 79 failed and non-failed firms during the years 1949 to 1963. Using Cash flow / sales, Cash flow / total assets, Cash flow / Net worth, Cash flow / total debts as cash flow variables. He found that both in the short-term, and in the long-term, the cash flow to total debt ratio was the best single predictor with a 13% mis-classification error 1 year prior to failure, while the misclassification error for year 2 to 5 prior to failure were 21%, 23%, 24%, and 22% respectively.

Blum [1974] used 115 failed industrial firms and 115 non-failed firms randomly chosen from the January 1969 index to COMPUSTAT during the years 1951 to 1967. He reported that the classification accuracy of the model was 70%-97% from 5 to 1 years prior to failure, and cash flow / total debts variable generally received high rankings. Hold-out sample produced similar results. Altman, Haldeman, and Narayanan [1977] investigated cash flow / fixed charges and cash flow / total debts, and found that neither cash flow variables were significant in the best model, which had a 96% and 70% classification accuracy for the first and the fifth year prior to failure.

Norton and Smith [1979] employed cash flow / sales [CF/TS], cash flow/total assets [CF/TA], cash flow / new worth [CF/NW], and cash flow / total debts [CF/TD] as cash flow variables in applying linear multiple stepwise discriminant analysis. They revealed that CF/TA and CF/TD were part of the best discriminant model three years prior to failure. CF/TD was identified by regressions for inclusion in second discriminant analysis. The model achieved 87.7% to 66.7% classification accuracy 1 to 4 year prior to failure. A source of information about company failure is a corporate strategy analysis which will consider and emphasise the cash flow analysis [Foster, 1986]. Accordingly, one might expect that cash flow data are primarily relevant in prediction of company failure. A number of succeeding studies also proved cash flow / total debt to be useful in predicting bankruptcy.

In Mensah's [1983] study, the cash flow / net worth was the most important ratio in discriminant (historical cost) model. The cash flow / total debt, cash flow/total assets, and cash flow / total sales variables loaded highly on factors not common to both failed and non-failed ex-post samples. However, those studies described above generally defined cash flow as income plus depreciation. The purpose for those above studies to employ cash flow ratio not only try to improve predictive ability but also react to prevailing declaration that cash flow has played a important role in predicting bankruptcy. The following studies generally defined cash flow as income adjusted for all accruals accounts.

Gombola et al. [1983] used 52 failed and 52 non-failed firms from Dun and Bradstreet's Business Failure Record during 1965 to 1977 period. Cash Flow From Operation [CFO] is defined by FASB as "working capital provided by operations plus or minus changes in the noncash working capital accounts, except for short-term debt (seasonal bank loans, non-trade notes payable, and the current portion of long-term debt). He used factor analysis and found that net income plus depreciation and working capital from operations had high correlation with one another. An eighth factor, cash flow, results from the factor analysis, in addition to the seven listed by PMC and PEMC. Cash Flow From Operation [CFO] ratios load on a separate factor during 1973 to 1977 period. Scores on CFO factor are significantly different between failed and non-failed firms only in first year prior to failure, and probit model is significant only for first year prior to failure. Decrease in predictive accuracy upon deletion of CFO factor is not statistically significant. Therefore, CFO is not significant.

Casey and Bartczak [1984] performed a univariate study of the predictive ability of cash flow from operation [CFFO] and related cash flow ratios. CFFO was defined as working capital provided by operations plus or minus changes in the non-cash working capital accounts, except for short-term debt. They examined 290 companies, 60 of which had filed petitions for bankruptcy during the period 1971-1982, and matched them with 230 viable (at least "non-bankrupt") companies chosen at random from similar industry groupings on the COMPUSTAT industrial tape. Three variables were computed: Operating Cash Flow [OCF], operating cash flow / current liabilities, and operating cash flow/total liabilities.

They found that although all of the variables were fairly good at classifying bankrupt companies, the classification rates for the bankrupt companies were 90%, 92%, 83%, 88%, and 85% from the first year to fifth year prior to failure using operating cash flow. The corresponding classification rates for the non-bankrupt companies were poorer than for the bankrupt companies, 53%, 44%, 63%, 35%, and 40% for the first year to fifth year before failure. Therefore, they reported that operating cash flow data for a five year span could not discriminate between the non-bankrupt and bankrupt firms accurately. Furthermore, a combination of six traditional accrual-based multivariate discriminant models, including debt-to-equity and profitability ratios, forecasted bankruptcy more accurately than any single operating cash flow ratio when they were looking at overall accuracy.

They hypothesized that cash flow from operation [CFFO] variables were not appropriate in identifying non-bankrupt firms due to the distributions overlapping considerably, making it difficult to distinguish between two groups, since successful companies may be losing cash flow due to taking advantage of market opportunities or expanding their plants. Adding specific working capital variables, such as the change in account receivable, could dispose of this perplexing element. However, in their stepwise discriminant analysis, they find that CFFO to total debt is a significant predictor variable only one year and two years prior to failure but not in earlier years. Casey and Bartczak raise a question about the presumed value of cash flow for analyzing and forecasting a company's performance.

Casey and Bartczak [1985] set out to determine whether the marginal predictive content of operating cash flow variables used in combination with accrual-based ratios to multivariate accrual models can lead to more accurate predictions of bankrupt and non-bankrupt firms. Discriminant analysis applied to a sample of nearly 300 companies raises serious doubt about the reliability of operating cash flow as a financial indicator. 60 companies, bankrupt during the period 1971-1982, were matched with 230 non-bankrupt firms selected at random from similar industry groupings on the COMPUSTAT Industrial Tape, with half of the sample used for derivation and half as a hold-out. Casey and Bartczak [1985] found that:

1. None of the results improved the percentage accuracy obtained by the addition of cash flow variables, either in a practical or a statistically significant sense for the bankrupt, non-bankrupt, or total groups of firms.

2. The finding that Operating Cash Flow [OCF] data do not accurately distinguish between healthy companies and dying ones raises a question about the presumed value of cash flow data for analyzing and forecasting a company's performance.

3. Operating Cash Flow [OCF] data are not the Holy Grail that some have made them out to be.

They noted that operating cash flow data does not provide significantly greater power over and above accrual-based ratios. OCF could possibly perform better in corporate acquisition, loan defaults, and dividend omission aspects. This is probably because these decisions are less subject to the influence of political and/or other extramarket forces.

Gentry, Newbold, and Whitford's [1985a] purpose was to determine whether cash-based fund flow ratios can successfully classify failed and non-failed firms. They initially redesigned the model to have only eight major components. The eight net funds flow components are funds from operation (NOFF), working capital (NWCFF), financial (NFFF), fixed coverage expenses (FCE), capital expenditure (NIFF), dividends (DIV), other asset and liabilities flows (NOA & LF), and the change in cash and marketable securities (CC). Each component is divided by total funds flow and used in a logit analysis with a derivation sample comprised of 33 failed firms (located in COMPUSTAT Annual Industrial Research File) and 33 non-failed firms matched by size, industry and specified three years of data over the 1970-1981 period. The inflows and outflows are characterized as due to one of eight comprehensive causes. The independent variables are the components of changes in cash.

Results from a derivation sample using one year before failure showed that the funds flow model correctly classified 79 percent of the failed firms and 88 percent of the non-failed firms. A validation test, using a hold out sample of 23 companies rated by a financial service as financially weak and 23 matched non-weak firms, they were also able to classify 70 percent and 74 percent of financially weak and non-weak firms, based on data one year prior to failure. The primary finding is that cash-flow-based funds flow components offer a viable alternative for classifying failed and non-failed firms. However, the dividend funds flow component was statistically significant variable in the failed and non-failed classification model. Cash Flow From Operations [CFFO] derived from Casey and Bartczak [1984] in their study did not improve the classification of failed/non-failed companies.

Gombola, Haskins, Ketz, and Williams [1987] examined whether CFFO is important in predicting corporate failure after the mid-1970s. Gombola, et al evaluated the Casey and Bartczak [1985] and Gentry et al. [1985a] data set and did not find CFFO to be a predictor of failure. It would be due to the high collinearity between earnings and cash flow. They tried to test whether cash flow is a significant indicator of failure or not in bankruptcy prediction. Gombola et al. identify 77 failed firms in the period 1967-1981, and a control group of 77 non-failed firms was also examined. The sample was divided into early (1967-72) and late (1973-81) subsamples. The discriminant models examined were estimated by using combinations of the five variables with the highest loadings on underlying financial dimensions and four alternative funds flow measures.

They conclude that cash flow from operation [CFFO] (calculated as working capital from operations plus / minus changes in current liabilities and current assets other than cash) is not significant, which is consistent with Casey and Bartczak. The marginal predictive ability of CFFO is not significant in all four years as well. They explained that the reason is probably due to lack of adequacy in CFFO information with their simplistic estimates based on income plus depreciation.

3.3.2 Adjusting Financial Ratios: Price Level Adjustments.

Many studies report that financial statement-based variables of distressed firms behave over time differently from those of non-distressed firms. Accordingly, it may be necessary for analysts to adjust financial ratios to obtain the greatest information value. Adjusted general or specific price-level adjustments variables may be useful to examine the value for bankruptcy prediction of historical data. Foster [1986] reported that

> "To date, there is very little evidence that making adjustments to place all firms on a consistent set of accounting methods, or using a non-reported accounting method, significantly improves the predictive ability of multivariate failure prediction models"

Ketz [1978] compared General Price Level [GPL] and historical cost ratios in the prediction of bankruptcy. He employed stepwise discriminant analysis, which discards some ratios of the data sets. Ketz's result indicated that such methods can be effective in developing models that discriminate between bankrupt and non-bankrupt firms. He finally concluded that general price level data were useful when relative costs of mis-classification were considered.

Altman, Haldeman, and Narayanan AH&N [1977] selected 53 failed firms and a paired sample of 58 non-failed firms by the industry group and year. They made effort to use footnote data and did several accounting adjustments to the firms in their sample. For example, they capitalized all non-cancellable operating and finance leases, deducted goodwill and intangibles from assets and equity, and consolidated captive finance companies with the parent company accounts as well as the information would allow. The pooling of interest method was used. The purpose for these adjustments was to make the model more compatible with recent financial reporting requirements imposed by the Financial Accounting Securities Boarding [FASB] or the Securities Exchange Committee [SEC]. Nevertheless, they did not disclose their adjustment procedure.

Norton and Smith [1979] endeavoured to determine whether general price level (GPL) financial data would give better predictive power than historical cost data. They concluded that in spite of the sizable differences in magnitude that existed between general price level and historical cost financial statements, little difference was found in the bankruptcy predictions. General price level data were shown to be consistently neither more nor less accurate than historical cost (HC) data for prediction of bankruptcy [p. 72]. Because stationarity issue has not been investigated in the bankrupt prediction, they suggest that the ex-post discriminating ability is often examined to provide an indication to the future usefulness of different models.

Mensah [1983] examined the usefulness of specific price-level adjusted (SPL) ratios by adjusting financial statement data using published specific price level indices. An original (ex-post) sample of 60 firms was used to derive the best model, and a hold out (ex-ante) sample of 46 firms was used to derive the validation examination. The companies in the ex-post sample filed for bankruptcy during the period of 1975 to 1978; those in the ex-ante sample in the 1979 to 1980. Non-failed firms were matched according to three-digit SIC industry classification and size measured in terms of sales. The initial set which consisted of 39 financial ratios, was used to avoid any inadvertent bias popular in the previous studies in the literature. Three types of models, one using HC ratios, another using SPL ratios, and a combined (HC/SPL) model with both ratios, were derived to develop three different models which can examine the possible predictive accuracy of the respective models in either the ex-post sample or ex-ante sample.

Mensah calculated the mean and standard deviation of each financial variable from Historical Cost (HC) data and estimated SPL values for the ratios. Two multivariate statistical methods, multiple discriminant analysis and logistic regression, were employed to derive the ex-post classification and the ex-ante prediction results. Since ex-ante prediction and not ex-post classification was the focus of his study, three different approaches, full model (selected stepwise), reduced collinearity model, and factor analytic model, were tried to determine their impact on the ex-ante prediction results. Mensah found the classification success of any single model was not statistically different from another's.

However, when mis-classification costs were considered, the SPL model was better than the other models. In a logit analysis, the estimated probability derived from the ex-post sample applied to the same hold-out sample, the model combining HC and SPL data was superior over a wide range of possible costs per type of mis-classification when costs were again considered. Mensah concluded that the evidence weakly supported the use of SPL data in bankruptcy prediction. In an overall sense, accuracy rates ranged from 63% to 92%, the volatility measures of SPL data were helpful in improving failure prediction. He realized that his study is subject to several limitations. Conclusions from the small hold-out (only 11 bankrupt firms) sample size bankrupt prediction might not be general. His findings can only be applied to the actual periods covered due to the stationarity issue. No formal failure prediction theory can be improved by his findings

3.3.3 Selecting Macro-Economic Variables

Foster [1986] has suggested that multivariate models could increase predictive power by incorporating macro-economic variables. In an attempt to discover which macro-economic variables are most related to bankruptcy, Rose, Andrews, and Giroux [1982] examine economic cyclical indicators, leading and coincident indicators, identified by the U.S. Department of Commerce (USDC) and the National Bureau of Economic Research (NBER), as well variables suggested by theories of the business cycles. It would seem reasonable that macroeconomic indicators also may be helpful predictors of individual firm failure, since any given firm may have a higher propensity to fail in times of economic recession than in times of economic prosperity. The most important leading indicators used by Rose, et al are:

1. Composite Index of Leading Indicators; and
2. Stock Prices: S&P 500 Composite Stock Price Index and Dow Jones Industry Average.

Among the key coincident indicators developed by NBER and USDC and employed in their study are:

1. Composite Index of Coincident Indicators;
2. Gross National Product in both current and constant dollars;
3. Personal Income;
4. Personal Consumption Expenditures; and
5. Unemployed rate

Both leading and coincident indicators of the business cycle may be helpful because indices of failure are inclined to be lagging indicators of the cycle.

A second possible approach is to employ variables suggested by economic theory focused upon multiplier interaction models and dynamic structural models of the cyclical process. Three groups were included:

1. Supply or cost-push theories;
2. Monetary theories; and
3. Savings-investment theories.

A regression of the foregoing cyclical indicators and variables suggested by the business cycle literature comprised quarterly failure company data period from 1970-1980 in the form of failures per 10000 firms. SAS forward selection was utilized to analyze the impact of macro-economic factors on the failure index and this resulted in a six-variable model incorporating lead-lag relationships had an high R squared of 0.912 and F values from the estimated equations. Six variables were significant for this equation. Two interest rates (prime bank rate and ninety days treasury-bill), the S&P 500 composite index, and three non-monetary demand and supply factors (gross private domestic investment/GNP, profits after tax/income originating in corporations, and retail sales / GNP).

Macro-economic data in general is not accurate. Jones [1987] suggested that:

> "Incorporating national economic indicators directly in a cross-sectional sample will not be helpful in discriminating between failing and non-failing firms, since each firm will be operating under the same conditions. It may be useful however, to incorporate regional indicators or industry indicators if there are legitimate regional or industry differences between firms."

Even from a national perspective, however, macroeconomic variables may be useful in forecasting, since it will be useful to predict the general probability of bankruptcy (i.e., the prior probability) before assessing the likelihood of individual bankruptcy. Thus, selecting macro-economic data used in a study should be as accurate as is available on the basis of the characteristics of corporate, industry, and regional indicators. Nevertheless, using macro-economic variables may be helpful in forecasting, since it will be useful to predict the general probability of bankruptcy.

3.3.4. Using Information Decomposition Theory

Decomposition measures are derived from information theory. Information theory has been applied to accounting research in a number of studies. Theil [1969] applied information theory for financial statement analysis in particular. He was soon followed by many authors, such as: Lev [1969], Walker et al. [1979], Booth, [1983], and Lincoln [1984]. Information theory was developed particularly in the field of communications engineering studies and is defined in probabilistic terms. The main components of information theory include a specific set of events with a known prior probability of occurrence and a message used to revise the prior probability to a posterior probability [Babich, 1975, p. 172]. Theil [1969] defined information theory based on the financial statements. Theil states that

> "Information theory provides a practical and, in fact, quantitative measure of the information content of such a message, defined in terms of the probability P before the arrival of the message".

Lev [1971] developed a thorough approach to the application of information theory, through decomposition measure, to financial statement analysis. His 1971 study suggested that significant changes (subjectively determined) in the proportional relationship among items of the financial statements may indicate future bankruptcy. He measured the information content of current and fixed assets, current and long-term liabilities (including owners' equity) so as to determine any systematic difference between failed and non-failed firms in the information content. He found that

1. The average information measures were significantly larger for failed firms than for non-failed firms;

2. It can be proved that measures indicate the stability of the relative contribution of financial statement items over time. Failing firms are expected to endure

larger and more change disproportionately in their current assets, fixed assets, current liabilities, and long-term liabilities than non-failing firms;

3. The balance sheet information measures consistently display the best predictive ability. Non-failed firms contained higher information measures than the failed firms.

4. The comparison of non-consecutive years tests indicated the longer the interval between balance sheet dates, the higher the predictive power of the information measures. Information measures can be used to discriminate between failed and non-failed firms for as much as five years before failure.

He concludes that no trend was detected in the information measures over the five-year span. However, since information decomposition measures are established from balance sheet data they may be compared only with balance sheet ratios. They are distance measures and therefore are directionless. Hence, they cannot discriminate between an increase and a decrease in a specific item or between very successful and failing firms without additional indicators [Theil, 1969, and Lev, 1971].

Booth [1983] defined insolvency as the control of assets exercised for the benefit of creditors. He used discriminant analysis to test two hypotheses. The first hypothesis is that:

A. The decomposition measures of failed firms are larger than those of non-failed firms based on:

   1. The relative value of decomposition measure between failed and non-failed firms for each year, and

   2. The relative average value of each decomposition measure for all possible pairs.

The second hypothesis stated that:

B. The coefficients of variation of the decomposition measures of failed firms are larger than those of non-failed firms based on:

1. The assets decomposition measure for the average, first , and fourth years before failure;

2. The equities decomposition measure for the average and all years before failure; and

3. The balance sheet decomposition measure for the average and second, third, and fourth years before failure.

Booth used discriminant analysis to test these hypothesis. 85 per cent of the sample was correctly classified. Type I error rate (18%) was higher than that of Type II (12%). Thirteen pairs of failed and non-failed firms were matched from the year 1973 to 1979 to test validation sample. He found that the classification accuracy was only 50 percent, which is equal to chance. Type I and II error rate was equal (50%). He concluded that decomposition measures as variables in the model led to a significant inability to successfully classify non-failed firms. He speculated that the mis-classification of non-failed firms may have resulted from their diversity, particularly the inclusion of growing firms.

Booth and Hutchinson [1989] attempt to empirically investigate whether decomposition measures can distinguish between growing and failing firms. A group of 35 firms, pair matched by industry and size during the period 1963 to 1979, were selected from Sydney Stock Exchange Research Department (SSERD). The total balance sheet, total assets, total liabilities and total equities were calculated for the decomposition measure. They tested three hypotheses in an attempt to discriminate between failed and growth firms. They conclude that the decomposition measure analysis of balance sheet changes over time is unable to successfully discriminate between failed and non-failed firms. The stability of the assets decomposition measure is consistently less for growing than failed firms.

3.4 Selection of Dependent Variables

3.4.1. Bankruptcy As the Dependent Variable

Nearly all of the studies analysed here use bankruptcy as the dependent variable of interest. Jones [1987] said that some users of bankruptcy prediction models are interested in bankruptcy primarily as a signal of severe financial distress. For example, investors and creditors may seek to avoid the losses associated with financial distress. A researcher may choose to use bankruptcy as a surrogate for financial distress rather than income level or liquidity position in order to avoid the tautological problems that could result when predictor variables and the dependent variable are based on the same financial statement (p. 133). Care must be taken when using bankruptcy as the dependent variable. Because companies that file for bankruptcy not only because they are experiencing serious financial difficulty but also for some other reasons. For example, a company may voluntarily file for re-organization or merger reasons.

3.4.2. Data Collection Sources

In research concerned with all firm types, a list of bankrupt firms is frequently derived from the Wall Street Journal Index (for example, Elam [1975]; Ohlson [1980]; Frydman, Altman, and Kao [FAK, 1985]), from Moody's Industrial Manual (for example, Hamer [1983]), from COMPUSTAT Industrial Tape (in the U.S.) or Datastream and Extel card (in the U.K.).(For example, Keasey and McGuinness [1990], who examined firms deleted from the Datastream), to derive the sample of failed firms. Samples drawn based on the Wall Street Journal Index or Datastream are likely to exclude small firms because only medium and large size firms will be listed in the Wall Street Journal Index or Datastream. The importance of this bias is undeniable since small firms are especially prone to bankruptcy. Similarly, financial data are usually acquired from the Datastream or Extel card database, which will not include small firms. However, the data base is criticized, when COMPUSTAT is used, for self-selection. A favourite working source of data is that it can provide a database easily retrieved by computer, which excluded very small firms. Thus, there is a trade-off between a universal data bank and an easily accessible data bank. Research studies admit this limitation that any conclusions should be limited to firms from a homogeneous population. Meanwhile, researchers should ensure that the sample has no major industry and time specific sampling biases so that the model is suitable to the decision makers' context.

3.4.3. Timing of Data

The timing data for sample selection appears to be committed mainly by the need for satisfactory sample with which to work in model development and analysis. Awareness is necessary when collecting financial statement data disclosed near to the date of bankruptcy filing. Shelton [1987] stated

> "having a long timing of data for sample selection is criticized since different economic conditions may have been prevalent within the time span. Combining data from different economic conditions is perceived to threaten the validity of the models".

Ohlson [1980] criticized data collection which does not compare the company's bankruptcy date with the availability of company's final financial statements. The annual report most recently published prior to bankruptcy may have become available only after bankruptcy was filed. He found that the bankruptcy filing was disclosed in the annual reports (for the fiscal year before bankruptcy) for 17 percent of 105 bankrupt fiirms. As a consequence, the average lead time span between the date of the fiscal year of the last relevant report and bankruptcy is quite long, approximately thirteen months in Ohlson's study.

3.4.4. Matching Criteria

Once a sample of bankrupt firms is derived, a control sample of non-bankrupt firms must be drawn. For comparison of the population of failed firms with those of non-failed firms, researchers should identify those non-failed firms. However, failed firms are often disproportionately small and concentrated in certain failing industries. The following popular matching criteria are usually applied :

1. Data availability that permitted the calculation of ratios across firms and across years;

2. One failed firm was matched with one or two surviving firms having the same industrial sector and appropriate asset size, and the corresponding year.

3. Industry classification was that used by Datastream or EXTEL (in the UK) based on homogeneity of production focused on the enterprise Standard Industrial Classification (SIC) scheme for defining industries;

3.4.5 Reasons For Using the Matching Approach

Beaver [1966] recommended that the matching approach design was selected to help provide a "control" over factors that otherwise might blur the relationship between ratios and failure. As noted by Lev [1974, p. 141], the paired-sample method permits researchers "to control for various factors that are believed to be unrelated to the phenomenon investigated". The size of a firm is also generally regarded as having some influence on the probability of failure. Therefore, most studies in this prediction area have attempted to eliminate this effect by matching according to the book value of total assets, sales, and corresponding year. Altman [1968] applied the MDA to the classification of two new samples. One sample was of pairs matched as to assets; the second sample was unmatched. The accuracy rate for the matched sample calculated at 96 percent for one year prior to bankruptcy, while the accuracy of the unmatched sample came to only 79 percent.

Jones [1987] states that if the nonbankrupt firms were drawn at random, there would probably be substantial differences between the two groups in terms of industry and size. The result is that the model attempting to discriminate between failing and non-failing firms may actually be distinguishing between large and small firms, or between railroads and other industrials. For example, Beaver [1966]; Izan [1984]; Zavgren [1985]; and Platt and Platt [1990] used the frequent criteria to control for these perplexing influences by matching the failed firms with non-failed firms according to size, industry, and corresponding financial statement year. Such an approach deals with the issue of how to define the size of the non-failed sample. Ideally, the control sample should be a random sample of non-failed firms with data covering the same years as the failed sample. This rarely happens for a number reasons.

Keasey and Watson [1991] stated that (1) it is unclear what size of sample the random selection should have, (2) a random selection would be likely to result in the non-failed sample containing different proportions of firms from particular industries and size bands than the failed sample. Hence, differences in the values of the independent variables between the samples could not be solely attributed to failure/non-failure. Keasey and McGuiness [1990] also stated that

> "Whilst there is debate over the benefits of matching, given the actual occurrence of failure within an economy, we adopted a matching procedure for two reasons. First, it keeps the data set manageable in terms of overall size. Second, the matching process offers a method of determining the sample of non-failed firms. It is not clear what criteria should be used if a matching approach is not adopted." [p.120]

Amit and Livnat (1990) state that an alternative classification method which explicitly considers economic attributes of every business segment of a conglomerate firm may enhance the cross-sectional analysis of financial ratios. Of course, one approach that seems intuitively appealing is to match each conglomerate firm with other conglomerates which operate in the same industries, have similar composition of assets, and similar economic characteristics.

Keasey and Watson [1991] state that most studies have dealt with sample derivation problem by matching the non-failed firms to the failed firms in terms of industry and size. Matching approach overcomes the issue of how to define the size of the non-failed sample. However, this solution also rules out size and industry as predictor variables. Additionally, the use of matching sampling will not reflect population proportions, as would be the case with random sampling. Palepu [1986, p. 31] points out that the use of non-random samples has three drawbacks that make the reported predictive results unreliable. Although non-random sampling does not affect the relative ranking of firms in terms of potential classifications, it does lead to biased classification probabilities. Nevertheless, in an empirical context Zmijewski [1984] found that, while non-random samples gave rise to biases, the biases did not appear to materially affect the overall classification rates. As Palepu [1986, p. 8] says, "hence, if the purpose of the estimated model is only to rank probabilities, the above bias is unimportant. However, the estimated parameters are to be used to test hypotheses, the bias and inconsistency become important". Strict random sampling also leads to a sample largely comprising of non-acquired companies. From an estimating procedure perspective, this is inefficient. Hence, Barnes [1990] commented that most empirical studies decide to use a sample with an equal number of targets and non-targets. Unfortunately, Zmijewski [1984] and Palepu [1986] did not address the stability problems. The clear implication is that they do not consider it to be a problem.

However, there is considerable evidence that matching by industry, size, year, or other criteria is an appropriate control mechanism when the research objective is to examine the statistical significance of individual causal variables. For example, Dun & Bradstreet [1985] gives the following industry information on 1983 failure rates. [see Table 3-5]. Foster [1986] suggested that differences do appear across industries in their observed failure rates. Incorporating these differences into a discriminant model could well improve its predictive ability. Finally, Keasey and Watson [1991,p95] suggest that the use of sample derivation procedure is to ensure that non-failed firms and failed firms have the same years' data because failing firms are likely to delay the submission of their accounts, and this is a particularly acute problem with small failing firms, since it is not uncommon for the accounts relating to the 2-3 years prior to failure never to be produced or to be unavailable until after failure occurs..

Table 3-5 Failure Rate Per 10,000 Operating Concerns

Manufacturing		
	Furniture	211
	Transportation Equipment	180
	Textiles	126
	Food	93
	Paper	71
Retail		
	Infant and Children's wear	227
	Sporting goods	116
	Men's wear	112
	Eating and Drinking places	65
	Department stores	34

Source: The Dun and Bradstreet Corporation [1985]

3.4.6 Sample Selection

The fundamental procedure to the classification of companies as failed or non-failed was to define failure for the purpose of the study and to subjectively distinguish particular companies by this definition. Various definition of failure have been presented by different authors. For example, Altman [1983] defines failure by economic criteria to mean that the realised rate of return on invested capital is significantly and continually lower than prevailing rates on similar investments. The popular criteria used for sample selection were the following procedures:

1. Failed firms and non-failed firms were matched in terms of the years of accounts used to form the financial ratios.

2. Matching took place in terms of company size defined in terms of total assets.

3. The firms were matched in terms of industrial sector defined in terms of the FT All share industrial classification.

3.4.7 Selection of Non-Failed Firms

Once a sample of bankrupt firms is obtained, a control sample of nonbankrupt companies must be drawn. Gilbert et al [1990] used three groups of firms, (1) a 76 bankrupt firms, (2) a random 304 non-failed firms (each failed firm was randomly assigned four non-failed firms), and (3) 304 distress firms (four distressed firms were formed by randomly assigning to every failed firm), i.e., firms which are identified as being financially weak but which did not go bankrupt, to discriminate between non-failed healthy and non-failed distressed firms. The distressed group contained firms that had negative cumulative earnings (income from continuing operations) over any consecutive three year period between 1972 and 1983 and this separated non-failed healthy from non-failed at risk firms. They concluded that a bankruptcy model developed using a bankrupt/random estimation sample can not distinguish firms that fail from other financially distressed firms. Further, the findings also demonstrated that bankruptcy models estimated from a sample comprising of a pool of problem firms performs poorly.

Altman [1968] used a hold-out sample of failed-firms and marginal non-failed firms, selected on the basis that each company must have suffered losses in two or more of the previous three years. The model correctly identified 79 percent of the non-failed firms. Gentry, Newbold, and Whitford [1985a] used a hold-out sample of financially weak and non-weak firms based on National Organization's Credit Watch list. The model correctly classified 70 percent weak firms and 74 percent of the non-weak firms. Taffler [1982] has argued that the control sample should only include non-failed healthy firms because non-failed distressed will have similar characteristics to the failed sample.

The number of failed firms, in the real world, are very small compared to the number of non-failed firms. If a random sample were selected from such a population, it would include an overwhelming majority of non-failed firms. The user of the failure prediction model only needs to ensure that the sample used to derive the model has no major industry biases because of its time frame. For example, in the early 1980's, the toy industry in the U.K. lost a large number of firms. It is likely that a failure prediction model developed from data for that period will be biased by a toy industry effect.

If non-failed firms were collected at random with data obtaining the same years as the failed firms, there would be likely to result in the non-failed sample including substantial differences proportions of firms from particular industries and size value than the failed firms. The result is that the model undertaken to distinguish between failing and non-failing firms may actually be discriminating between large and small firms (size effect), or between textiles and investment sectors (industry, and accounting method effect) (also see section 3-4-5). In order to keep the dataset more manageable in terms of overall size and offer a proper method of determining the sample of non-failed firms, therefore, most previous studies have selected non-failed firms on the basis of a matching approach.

Ideally, the control sample should be constructed by a random selection of non-failed firms. A stable and rigourous predictive model will be built from data from one sample of initial firms and will be tested using data from a validation sample inclusive of different firms. This approach is focused on a model's external validity and its likely practical value for decision-making. However, the generally accepted matching approach was used to select the non-failed firms as follows:

1. Identifying the industry of a failed firm and matching with non-failed firms with the same industry code.

2. Within the same industry group, conditionally select the non-failed firm whose asset size is approximately the same as that of the failed firms;

3. The non-failed firms are matched with the failed firms on the basis of the same corresponding year of financial statement.

3.5. Definition of Company Failure

3.5.1 Company Failure

It may be helpful to understand company failure by setting out briefly the steps involved in bringing a company registered under the Companies Acts to its end. This is can be effected by a winding-up, removal from the Register under the provisions of Section 652 of the Companies Act, 1985, whereby the Registrar has jurisdiction to strike off the Register the names of companies believed to be defunct, or by dissolution by Order of the Court in connection with a reconstruction under Section 427 of the Act. Three different kinds of winding-up are:

3.5.2. Compulsory Liquidation

A compulsory winding-up order in England is subject to a considerable measure of control by the Department of Trade and Industry, and an account of the liquidator's receipts and payments must be rendered to that Department every six months. When the account has been audited by the Department a duplicate copy is filed with the Court and is "open to the inspection of any person" [Company Act, 1985, S. 543].

Upon the completion of a compulsory winding-up the Court can make an order dissolving the company; in practice, however, such an order is seldom made. The Registrar subsequently strikes the name of the company off the Register under the section 652.

3.5.3 Voluntarily Liquidation

Voluntary liquidations may result either from a member's or creditor's voluntary winding-up order. A corporation may be voluntarily dissolved with the consent of the shareholders. The company must pay its debts in full within a period not exceeding twelve months; in such a case shareholders appoint the liquidator and control the liquidation. This may be due to the corporation's inability to pay its debts as they fall due, or total liabilities may be greater than total assets (other than to shareholders). In a creditors' voluntary winding-up, an account must be laid before a general meeting of the company and of the creditors, and while a return of the meetings, with a copy of the account, must be sent to the Registrar [Companies Act, 1985 S. 595].

3.5.4 Receivership

This is the state of being bankrupt and in the charge of the official receivers. When a resolution to wind-up voluntarily has been passed by a company, the Court, on the application of the company or any creditor or contributor, may make an order directing that the winding-up shall continue, subject to the supervision of the court

[Companies Act, 1985, S. 606]. Since creditors have had the right to apply to the court to determine any question arising in a voluntary winding-up. Consequently a Supervision Order is not frequently sought. Subject to the directions made by the supervision order which in England usually requires a report to be filed with the court every three months, the procedure, in practice, is similar to the case of a voluntary winding-up.

3.5.5 Definition of Company Failure

Many definitions of company failure are encountered in the liternature. The definition of company failure has varied across empirical studies and from country to country. While mean ratio values differ across countries, (reflecting country-specific economic conditions), they have been shown to be significantly different for healthy and financially distressed firms [e.g., Altman, 1984]. Failure , insolvency, and bankruptcy have all been used to describe the same phenomenon of ceasing operations even though the three terms have different meanings. Altman [1983] defines failure by economic criterion to mean that the risk adjusted rate of return is significantly and continuously lower than similar investments. He also mentions other economic criteria used, including insufficient revenue to cover costs, and return on investment being below the company's cost of capital. Insolvency is a technical term that exists when a firm cannot meet its current obligations. This lack of liquidity, also described as insolvency in the equity sense, may be a temporary condition but usually precipitates a formal bankruptcy declaration. Finally, bankruptcy is the act of a formal declaration by a firm to the courts to either liquidate its assets or to attempt a recovery program. As the criterion for bankrupt and non-bankrupt firms, it is not surprising that different authors have used different causes of failure definition.

Several studies have forcused upon the legal considerations when defining an unsuccessful or failed business enterprise. These range from somewhat all-inclusive approaches such as Altman's [1968, USA], where failure was defined as those firms that filed a bankruptcy petition under Chapter X of the national bankruptcy act. Wilcox [1976] used a Chapter X or XI bankruptcy petition as his criteria for failure.

Technical definitions of failure were also employed in past research. Beaver [1967] defined failure as: bankruptcy, bond default, an overdrawn bank account, or non-payment of a preferred stock dividend [p. 71]. Deakin [1972] defined failure "to include only those firms which experienced bankruptcy, insolvency, or were otherwise liquidated for the benefit of creditors" (p. 168). Foster [1978, USA] defined the business failure as "declining share of major product markets, deferment of payments to short-term creditors, omission of a preferred dividend, and filing of a Chapter X or XI bankruptcy" [p. 462]. The Dun and Bradstreet Failure Record [1983] listed several prime causes of business failure, such as "inadequate sales, heavy operating expenses, receivable difficulties, inventory difficulties, excess fixed assets, poor location, and competitive weakness". Taffler [1982, UK] defined failure as "receivership, voluntary liquidation (creditors), winding up by court order or equivalent" (p. 343). El Hennawy and Morris [1983, UK] defined failure as "a business which was liquidated, wound up by court or to which a receiver was appointed". Molinero and Ezzamel's [1991, UK] classification of failure as compulsory liquidation, voluntary liquidation, or receivership.

However, Chapter XI of the USA Bankruptcy Act is a voluntary proceeding in which a firm continues to operate while it attempts to work out a plan either for the payment of its debts or for a reconstruction of debtors' claims. When a firm files for bankruptcy on the basis of Chapter XI, the court provides a firm protection from lawsuits and from mortgage foreclosure. Under a USA Chapter X Bankruptcy Act filling, a trustee appointed by the court takes responsibility for operating the firm. Filing of a Chapter X or XI bankruptcy does not necessarily mean that the company is to be liquidated.

Companies can appear again from bankruptcy proceedings as active survival and thereafter become fruitful and productive firms in their industry.

Foster [1978, USA] defined a Chapter X or XI in the business failure as very similar to the definition of receivership in the above section. Nevertheless, the symptom of failure in the bankruptcy sense indicates a incessant rather than a short condition. Any firms detecting themselves in the distress situation in which its total liabilities exceed a market value of total assets. This symptom is due to financial failure. Most young and small businesses' failures are heavily influenced by higher fluctuations of economic and interest on loan. For example, the inability of a firm to make a profit, the net income is not enough to pay the wages. In other words, the stage of impending approach is near to business failure.

Any definition of failure requires theoretical underpinning. Lack of conformity among studies in defining of failure means that it is inappropriate to compare the models developed, either directly or indirectly. Given these differences, it would be better to develop specific models for different types of firm failure, providing the necessary data is available. Before constructing a failure prediction model, decision makers need to take note of whether the failure prediction model fits the decision context.

In this study, failure is defined to include companies which have gone through either compulsory and voluntary liquidation or receivership. Failed companies which were discontinued through mergers or consolidation were not included in this sample, nor were failed companies which faced financial insolvency but continued in operation. This criterion is based on the negative cumulative earnings income from continuing operation over any consecutive two year period between 1974 and 1985.

3.6 Summary and Conclusion

Most theory developed in the literature is primarily devoted to the choice of appropriate dependent or independent variables for the prediction of bankruptcy models and to the development of a theoretical mathematical model. Not many previous researchers have made an effort to develop a comprehensive model for financial failure theory. Therefore, theory of failure yet exists which can be utilised by predictive models. Lev [1974] suggests that the main research effort should now be directed toward the testable theory of corporate failure". Foster [1986] comments that "the absence of an economic underpinning to modeling has led to trenchant criticism of research on financial distress".

It is clear that variables other than traditional financial ratios have some predictive ability. The results of Casey and Bartczak [1984] and Gentry et al [1985a] show that there is some benefit from researching the predictive ability of the variability of the cash flows. Dambolena and Khoury [1980], Keasey and Wynarcyzk's [1986] used the profile of stability measures to improve the predictive results between failed and non-failed firms. Ketz [1978], Norton and Smith [1979] found that general price level adjusted ratios were useful for the prediction of firm failure. Mensah [1983] used specific price adjusted ratios to provide an incremental information over and above that furnished by historic cost ratios. Keasey and Watson [1986] in their small business firms study found that the current cost value did not improve the predictive ability of the models.

The choice of variables to include in models typically has been based on their use in previous empirical studies. At present, there does not exist an underlying theory relating variable selection with the characteristics of decision makers that model builders in failure prediction area can access. To improve failure predictive ability rather than to examine economic theories of failure process, or to produce a model of business failure which relies on financial ratios and a variety of other independent variables but rather not on the basis of the economic cycles and its management structure, has been the prime concern of researchers in this area.

The independent variables included in the selected model are often a small subset of those originally considered by the model builder. Foster [1986] suggests that "the model builder may believe that a variable should be included in a model but finds that it is not significant or is even excluded from a model. In his context, it is important to consider potential explanations for the variable being insignificant or excluded before deciding whether to re-estimate the model with the variable included".

The methodologies chosen in failed and non-failed studies have important limitations that should be considered in interpreting their results. Most prior studies have dealt with this limitation problems by matching the non-failed firms to failed firms in terms of industry and size. Such an approach shows the evidence that both industry and size groups contain critically different failure rates likelihood. Including these differences into a model could well improve its predictive power. The matching approach also needs to define the size of a non-failed sample. In the next chapter, we describe how important the economic and industry influences are in developing and examining the stability of a forecasting failure prediction model.

Chapter 4 Economic and Industry Influence

4.1. Economic Influences

Despite of extensive prior literature a sad feature of previous bankruptcy prediction studies using MDA of financial ratios is a lack of consistency both in the values of the coefficients reported and the relative importance of the ratios. Part of this inconsistency can be attributed to researchers' initial choices of different sets of ratios. Apart from the selection of different ratios in the final prediction models. Another methodological issue relates to economic influences. In particular, many studies have used methods which have ignored economic effects on the development of a model, and they pool data across different years without considering the underlying fluctuations of the economy. Economic fluctuations must have an impact on the forecasting accuracy of business failure prediction models.

Separating economic conditions into homogeneous periods may be a route for investigating the importance of this. Business cycles used to have two marked phases: prosperity and depression, or boom and slump, with "peaks" and "troughs" marking the turning points in between. Today, it is recognized that there are four phases of business cycles [Samuelson, 1976, page 253]. Each phase is characterized by different economic conditions (see section 4.1.2). For example, during the expansion stage employment, production, prices, money, wages, interest rates, and profits usually rise, while the reverse is true in recession.

4.1.1 The Definition of Business Cycles and Their Effects

Business Cycles (BC) consist of recurrent sequences of expansions, downturns, contractions, and upturns in a great number of diverse economic activities. These movements are both sufficiently diffused and sufficiently synchronized to create major fluctuations in comprehensive aggregates of employment, inflation rate, real GNP, interest rate, credit availability, and real sales.

Burns and Mitchell [1946] defined the business cycles as follows:

> "Business Cycles are types of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises; a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; the sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible into shorter cycles of similar character with dimensions approximating their own."

Given this statement, it would be reasonable to support the view that the survival of firms in general, and their tendency to fail in particular, would be influenced critically by the state of the business cycle. Rose, Andrews, and Giroux [1982] recommended macro-economic indicators may also be useful predictors of individual firm failure in the business cycle, since any given firm may have a higher propensity to fail in times of economic recession than in times of economic expansion. The fundamental hypothesis that guides the empirical analysis is that variables measuring the business failure rate are negatively correlated with changes in cyclical indicators. Thus, for example, poor business performance and lower profits are generally associated with a rise in liquidation when the business cycle remains in a recession or contraction stage. Therefore, one possible source of instability in multivariate models of bankruptcy is suggested by the fact that the rate of corporate failures rises sharply during economic recessions (Lev [1974, pp. 134-39]).

In contrast to recession or contraction, good business performance and net profits and the rate of growth of economic activity are also generally associated with a decline in insolvency when the business cycle stays in an expansion and recovery stage. In sum, changes in business cycles may to a certain extent influence the business failure rate. The relationship between business cycles and the business failure rate was distinguished by the macro-economic indicators, such as, real GNP, interest rate, inflation rate,...etc, in the analysis of company performance. An important issue then is whether : To omit the influence of the business cycle is to neglect a critical dimension of information.

Since policy decisions may be important for the survival or failure of a business, the analysis of the relationship between corporate performance and the economic conditions should be relevant to managers, auditors, consultants, creditors, and financial analysts. Previous studies which attempt to predict failure of the individual firm have utilized micro (financial ratios) and macro (economic information) as independent variables. It would seem reasonable that differentiating each failed firm based upon the different economic conditions may be a helpful approach to predict a company's failure, since any given firm may have a higher probability to fail in times of economic recession than in times of economic expansion or recovery. These studies constitute, then, a first step in identifying which firms belong to which phase of the business cycle based upon different economic conditions that may be helpful in determining which firms are affected by the different phases of business cycles so as to develop and examine a stable failure predictive model.

Johnson [1971, p. 1166-67], states that "ratios to failure do not contain (explicit) information about the intervening economic conditions....the riskiness of a given value for a ratio changes with business cycle...up till now". Johnson [1971] suggested that although ratios are usually compared with similar ratios for the same firm over time, or with ratios of like firms, neither the absolute levels of ratios nor their relative magnitudes can be evaluated in isolation. An analyst may seek to determine the riskiness of a firm by calculating a coverage ratio. However, the riskiness of a given value for the ratio changes with the business cycle and the liquidity of assets. Similarly, two firms with identical coverage ratios can differ in riskiness due to dissimilar investment opportunities. Without a standard norm, ratio comparisons are meaningless.

Altman [1971] adopted the change in Gross National Product (GNP), the change in Standard & Poor's Index of Common Stock Prices, and the change in the Nation's Money Supply (M-1A). These three economic indicators act as the independent variables in the development of a model. Unfortunately, the R^2 in Altman's model was only 0.19, indicating relatively little explanatory power from economic factors.

Argenti [1976] states that managers should consider economic change such as a devaluation of a major currency, an international monetary crisis, the inflation rate, the interest rate, the pattern of disposable income and so on. For example, inflation in the UK was a serious economic phenomenon. Severe inflation can bring firms to bankruptcy. Managers should consider this and conduct a careful scrutiny of the economic scene to determine what their next major economic hazard might be. The western nations seem to have become subject to a 4 or 4.5 year economic cycle; it is probable therefore that any firm that is not habitually looking ahead at least five years will not be adjusted to the fundamental rhythm of the economy in which it operates.

4.1.2. Changes in Real GNP Economic Growth

The long-term growth of the economy has been disturbed by periodic booms and cyclical collapses. The period from the Second World War until the early 1970s was one of continuously high employment, with only the mildest fluctuations in GDP, employment and unemployment. Since 1970 business recessions in the UK have become much more severe. There was a sharp downturn in 1973-75, and by 1977 unemployment had reached 5% of the labour force. The vacancy rate, which indicates the degree of labour shortage in the economy, was at an exceptionally high level in the boom of 1973. By 1979 the economy had recovered to about the same level of vacancies as in earlier boom periods. After that, there was a major slump, with unemployment rising from 5 per cent of the labour force in 1979 to 11 per cent in 1985. From 1979 to 1981, output and employment remained in a recessionary stage. For example, Altman [1971] states the two series to reflect economic growth : real GNP and firm profits. Growth in GNP is traditionally viewed as an overall indicator of national economic health. Corporate profit does not necessarily follow GNP, and any profits fall to the marginal firm is critical to its continued existence.

4.1.3. Shifts in Credit Availability and Interest Rates

Money, or credit availability, most certainly does impact on business failure. Most failing firms begin with operating difficulties illustrated by the loss or deterioration in market share. Most banks normally will not be willing to take any risk by lending funds to firms which are facing failure. Therefore, in a period of high interest and low credit availability; the probability of failure is increased. Rising borrowing costs and interest burden, greater difficulty in obtaining funds pushes weak firms past their breaking point. For example, during times of high interest rates, the company least likely to fail might have relatively few interest liabilities.

Rose et al [1982] state that interest rates cause fluctuations in the amount of business inventory investment and long-term capital spending. Interest rates and credit rationing are presumed to increase during the expansion phase of the cycle until a point is reached where current levels of private spending can no longer be sustained with available credit supplies at current interest rates. As spending falls, interest rates begin to decline and credit gradually becomes more readily available. Both business and consumer spending start to grow again and the volume of borrowing rises. Hence, the credit and interest rate effect is potentially an important influence on the total failure experience of all firms.

Argenti [1976] reported that one of the crucial reasons for bankruptcy is too much leverage - a high ratio of debt to equity. In the ten years between 1965 to 1975, the market value of debt to the market value of the firm grew hugely. There is a limit to what any company should borrow and that limit varies with the company and with general economic conditions. If there is a decline in the economy, the over-extended company is in trouble. Bankruptcy may happen at any time. In times of economic depression, high interest rates become very important when looking at a firm's leverage. For example, if a company has to use fifty percent of its profits to pay its tax, half of the remaining might go out in dividends, leaving inadequate cash to expand. When there is a decline in the economy, the company has to borrow money. Failure to renew borrowing or meet interest repayments force the company into immediate bankruptcy.

Mensah [1984] suggested that ratios helpful in predicting bankruptcy in this context are those relating to interest coverage, receivable intensiveness, liquidity, and long-term leverage. Such ratios in this study as R42, R36-38, R22-23, and R14 (detail see Appendix A). One of this thesis's subsidiary purposes is to investigate whether interest rate as a macro-economic variable improves the predictive ability of the model.

4.1.4 Changes in the rate of inflation

Inflation or deflation refers to the general drift upward or downward in prices, the exchange rates at which money is traded for all goods and services. The tendency for inflation to fall in recession and rise in expansion is not new. The rate of inflation affects the measures of performance and disposable profit of firms that have the same characteristics in times of static prices. Even when inflation has been steady its effects are sometimes surprisingly pervasive.

Mensah [1984] said that changes in the rate of inflation can affect firms either by increasing the costs of production and marketing. It is argued that inflation helps marginal firms by reducing competition and protecting inefficiency.

He stated that ratios that may be helpful in identifying firms likely to be affected by inflation are those relating to inventory intensiveness, profit margin, assets productiveness, and capital intensiveness.

Therefore, the inflation rate is one of the macro-economic variables used in this thesis.

El Hennawy and Morris [1983] stated that companies in general are more or less vulnerable at different stages in the economic cycles. Three economic indicators may be obtained from the Financial Times - Actuaries (All Share).

1. The trend in the stock market during a company's financial year.

2. Turning points (boom or slump) in the economy can be revealed by comparing the returns' first difference over successive (arbitrary) periods (month, 3 months or six months) prior to failure.

3. The level of uncertainty in the economy can be measured by the standard deviation of the market returns over the working days of a company's financial year.

Unfortunately, these variables did not enter any of the discriminant functions. They suggested that the relatively short time span [1960-1968] under scrutiny lessened the significance of any macro-economic influences.

Mensah [1984] attempted to examine the relative importance of how different macro-economic environments and their impact on the bankruptcy prediction models. A reason for suspecting instability is that the characteristics of external economic environments which might be expected to affect the financial condition of companies change over time. He employed the inflation rate as one of his three external macro-economic factors to determine the changes over time in his study. The classification in the estimation period displayed 88.1 per cent accuracy for the manufacturing companies in the recessionary period and 75.8 per cent for the manufacturing sub-sample in the expansionary period. Similarly, the model developed in the expansionary period as 85.5 per cent accurate in the estimation period and 72.6 per cent in the recessionary period. The author examined whether different models are appropriate for different industries in the same economic environment. The model correctly classified 88 per cent in the manufacturing sector in the recessionary periods and declined to 63.5 per cent in the retail sector in the cross-validation. In the recessionary periods, the model correctly classified 85.5 per cent in the manufacturing sector and 75 per cent in the retail sector.

Mensah concluded that (1) the accuracy and structure of predictive models differ across different economic environments. If sufficient data are available over different time periods, the classification accuracy may be improved; (2) different prediction models seem appropriate for companies in different industrial sectors even in the same economic environment; (3) the predictive ability may actually be improved by explicitly considering multicollinearity in the inter-temporal and inter-sectoral development of the models. Reducing collinearity may actually aid the general application of the prediction model.

Jones [1987] said that it may be useful to incorporate regional indicators or industry indicators, if there are legitimate regional or industry differences between firms. At the national level, however, macro-economic variables may be useful in forecasting, because it will be useful to predict the general probability of bankruptcy before assessing the likelihood of individual bankruptcy.

Business cycles and macro-economic variables influence business failure and they play a significant role in the failure process. Business cycles and macro-economic variables are included in this study because prior research of the business cycle and macro-economic phenomenon in each country have shown them as important.

4.2. Prediction Versus Stability

4.2.1 The Stability of Predictive Ability Over Time

Unless all data comes from the same period, there may be time series problems associated with collecting the data over more than one period. Besides, the classification process may not remain stable from one period to anothers [Richardson and Davidson, 1984]. Regarding the stability of predictive ability over time, there are many reasons why the model may not be stable over time. Barnes [1990, p. 76-77] in his paper states the following two reasons:

1. Given inflationary effects, technological and numerous other reasons, including changing accounting policies, it is impossible to presume the distributional cross-sectional parameters of financial ratios to be stable over time. Empirical proof supports such a proposition (for example, Deakin [1976], Frecka and Hopwood [1983], in the USA; and Barnes [1982], and Ezzamel and Mar-Molinero [1990], in the UK).

2. The model reflects the attitudes of acquisitive managers and their advisers as to which companies are, and which are not, takeover targets. This may also change over time, and in fact be quite volatile.

A number of researchers have used data from the time period immediately prior to failure to generate a discriminant function. After examining the predictive power one year prior to failure, they then test to see if the derived function can be applied to predict failure up to five years before failure. Joy and Tollefson [1975] (hereafter J & T) interpret prediction to foretell the future.

They argue that validation of the predictive content of the model requires validation outside the time period of the original sample. That is, if the model is estimated using data from time t to predict the likelihood of an event occurring at time (t+1), then data from a future period (t + 2) should be used in the model to predict whether an event will occur in the appropriate succeeding period to validate the model. They argue that many authors who employ a hold-out sample from the original sample period inaccurately explain their ex-post classification results as indicators of the predictive accuracy of the model.

The essence of (J & T's) argument is that in time series applications, a discriminant analysis model is only useful for prediction purposes if the underlying relationships and parameters are stable over time. Otherwise, the model and estimated error rates will only be valid for the specific periods examined. The results cannot be predicted beyond the original sample period with the same expected classification results. Therefore, unless a known process is concerned, a function derived from data in the ex-post period will be different and will yield different error rates from a function estimated in the ex-ante period.

Lachenbruch [1975] used a sample to examine the prediction over time where the predictor variables are parameters from a time series regression. The ex-post period classification accuracy may not perform well on the ex-ante period's data. Thus, Altman & Eisenbeis [1978, p. 186] note that it is inappropriate to pool samples across time periods because the basic cross-section relations among the means and variances are not stable over time. Unless stationarity exists, classification accuracy derived from outside the original sample time period will produce error estimates of questionable or only limited value.

Foster [1978] commented that most papers published previously arise from the retrospective or ex-post nature of the analysis used in the major studies, e.g., the estimation and the validation samples both include firms that are recognised to have failed on a set date. Thus, it is possible in the study to compare the financial ratios of failed and non-failed firms one year, two years, etc., prior to failure. Yet, in decision-making contexts, it would be necessary to make ex-ante or prospective predictions about the failure of current non-failed firms. To illustrate such analysis, Foster [1978] used an example Altman's [1973] study on railroad bankruptcy using an estimation sample during 1939 to 1970, and then subsequently used that to validate the Z score (1971). This predictive ability contrasts sharply with the 2 per cent mis-classification rate when compared with the accuracy rate of Altman's [1968] for the estimation sample. Therefore, the model is not quite stable over time if improper use of the industry relative ratios is made to cope with this instability problem.

Other work which shows the stability of predictive ability over time also includes Moyer [1977] who employed Altman's 1946-1965 original sample to develop a discriminant function which was then applied to the second sample during 1965-75. He reported that the predictive ability of the estimation model drops significantly. Lev [1971] and Dambolena and Khoury [1980] investigated the issue of inter-temporal stability. Lev found that financial statement ratios are unstable over time, especially those representing failing firms. Dambolena and Khoury had similar findings with respect to the ratios constructed from such numbers. Their results indicated that ratios of failing firms displayed a substantial degree of instability. For example, Wood and Piesse [1986] examined Altman's [1968], Taffer's [1981] and Earl and Marais [1982] models reported that they had poor predictive ability.

4.2.2 Ex-post Classification Problems

Developing failure prediction models in previous studies has resolved certain statistical problems. The models ex-post classification results one year prior to failure are fairly invariant with respect to methodology and ten or more percentage points higher than the model's ex-ante results. One of the inconsistencies between ex-post and ex-ante classification results is data instability over time. To be of any effective use in the future, a failure prediction model derived from data in one time period should also work in future time periods. J & T [1975] stated that successful ex post classification indicates that inference about the importance of the independent variables in the discriminant functions is warranted. A model is only appropriate for predictive purposes if the underlying relationships and parameters are stable over time.

Altman & Eisenbeis [1978] argued all that ex post classification really provides an index of the overlap among the variable distributions in the groups for the sample period. Moreover, if the relationships among the independent variables in the populations are not stable over time, then the problems of estimating error rates would carry over equally to determining the role of individual variables as well. That is, inferences about the role of independent variables would only be valid with respect to the sample period, and could not be generalized over time. The role of ex post classification suggests that comparison of classification results from within the sample period with those outside the same period may itself serve as a crude test for stationarity [Altman & Eisenbeis 1978, p. 187].

4.2.3 Pooling Data Problems

Some studies have tried to cope with the industry difference problem by using a matched sample design, pairing a failed firm with one or two non-failed firms of the same industry and size so as to reduce the industry effects. Examples include the models by Altman [1968], Blum [1974], and Zavgren [1985]. A number of studies have ignored the industry difference totally, and have merely pooled data from a range of different industries. These include Marais [1979] and Micha [1984]. Taffler [1984, p. 209] heavily criticises as inappropriate their type of methods applied without considering cross-sectional industry differences. He states that

> "the pooling of manufacturing and distribution firms in one model is likely to prove problematical in the UK environment as these have quite different financial characteristics."

In other words, any model formed without investigating the specific financial or product characteristics of the individual industry is liable to suffer from a deterioration of the classification results, and is subject to the criticism that it is carrying out pooling (heterogeneous) data without an appropriate adjustment, resulting in an invalid and inefficient model. The sample of failed firms involved pooling of data spanning a number of years in previous failure prediction studies because of a lack of a sufficient number of failed companies for statistical analysis.

However, in Altman's [1968] study, failures were selected over the twenty years from 1946 to 1965. A time series is stable when its basic statistical properties (for example, mean and variance) remain constant over the whole period of the time series concerned. For a stable series, the mean can be calculated and be equally applicable to any subset of the time series. For a non-stable time series, different subperiods will have different means. Although a mean statistic can be computed for a non-stationary series, it is not a meaningful measure of the central tendency of the entire time series. If the assumption of a series stability does not exist, the successive analysis will cause error bias, because the mean and variance of pooling data will not be same. In many cases, some adjustment to the time-series financial data will be necessary to attain a stable series. Altman and Eisenbeis [1978, p. 187] state this issue:

> "If the basic cross-section relations among the means and variances are not stable over time, then pooling of data in such a manner is also inappropriate and invalid".

Mensah [1984] showed that researchers typically pool data across different years without considering the underlying economic events in those years and model coefficients are unstable over time. The implication is that models estimated in a given time period are of limited usefulness when applied to a different time period. However, one of the objectives of this study forecasting is to include the industry relative ratio that is hypothesized to be the cause of the un-stable differences among time periods, in order to see if the performance of the adjusted model is clearly superior to the unadjusted model. It is also crucial to include macro-variables to test for economy-wide inter-temporal influences. Eg. Cressy [1992] used a set of year dummies to do this. Some years were highly significant in his small business study, indicating that an economy-wide effect played an important role in small size business failure study.

4.3. Industry Influences

4.3.1. Industry Classification

In this section, part I, we describe existing Standard Industry Classification [SIC] as criterion to group firms into different industry groupings based on empirical commonalities. Part II, we describe cluster analysis to group each firm into different industry classification. Discussion will be introduced as follows:

Wippern [1966] employed the variability of a company's earnings as a proxy for business risk to examine the equivalent risk class hypothesis on the basis of equivalent degrees of basic business uncertainty. He reported that the variability in this proxy measure was as great within industry sectors as between outside sectors. The homogeneity of basic business risk is not accomplished by restricting samples to a specific industry. Gonedes [1969] extended Wippern's study employing a non-parametric technique and found only two industries among eight industries examined were homogeneous, in spite of significant variations were found between industries.

In looking for evidence that industry is a variable to control for, one study by Brown and Ball [1967] used regression analysis to evaluate company earnings on the basis of economic and industry influence. Four earnings variables were used: (1) net income, (2) operating income, (3) net income and after-tax interest expense, and (4) adjusted EPS. They concluded that (1) on average, approximately 35 to 40 per cent of the variability of a company's annual earnings could be ascribed to market-wide influences, and (2) on average, a further 10 to 15 per cent was attributed to industry-specific influences. With the remaining 50 per cent, variance was not taken into account in their model because of ignoring the industry and economic-wide aggregates in the presences of company-specific variables.

Williams and Goodman [1971] employed discriminant analysis to separate industrial firms from utilities and correctly classified 98 per cent. Next, a discriminant analysis was undertaken to test whether companies in five different industries could be differentiated. They found that classification accuracy was only 72 per cent. Unfortunately, they did not validate their model in a hold-out sample, the model appeared more or less sensitive to the different sample involved.

Sudarsanam and Taffler [1985] examined a sample of over 250 U.K. firms each classified into one of 14 industries based on (London) Stock Exchange Industrial Classification [SEIC]. Six financial variables were selected in their model so as to reflect a broad range of important characteristics relating to the economic, financial and trade structure of industries. They used multi-group discriminant analysis to examine if there was homogeneity of firms within each industry or heterogeneity across the 14 industries. They found that food, clothing, and chemicals sectors appeared to be more homogeneous with an average of over 40% of their firms correctly classified. The most heterogeneous are textiles, metallurgy and footwear with 15% fewer firms correctly classified. They then grouped the 14 industries into four meta industries (processing, engineering, textiles, and food); the model was able to classify correctly 69.7% of the firms into their four meta-group industry coding, approximately 29% being correctly classified by chance alone. They concluded that the classification scheme formulated by the London Stock Exchange Industrial Classification was only partially successful in grouping together companies according to the same economic, political, and trade influences.

Part two studies ignored the current existing Standard Industrial Classification [SIC] scheme and employed statistical techniques such as factor analysis and cluster analysis to determine the relevant grouping of firms. Cluster analysis aims at finding the groupings whose populations are not known in advance, to cluster different industrial sectors into new groupings based on observable and measurable financial ratios or performance criteria. (see Jackson [1983] for a description of these techniques). Most previous studies used published industry-based classification, because of their ready availability and their objectivity. However, it is worth evaluating that the basis of the selected grouping is consistent with the SIC codings. Examples of cluster or factor analysis based on groups are discussed as follows:

Gupta and Huefner [1972] support the statement that certain industries could be expected to have high values of a given ratio in comparison with other industries, and certain others could be expected to have moderate values, and so on. Hence, they employed a methodology (cluster analysis) which would classify homogeneous industry characteristics according to several financial ratios, based on their knowledge of the economic characteristics of the industry, into a number of broad groupings. They performed a separate clustering based on each of five ratios, and arbitrarily stopped the process when three groups of industry had been clustered. Companies could be grouped into different sectors when a variety of financial ratios were applied to cluster analysis. Companies in each sector were not consistently clustered into distinct groupings because the variability of different ratios were used as the criterion variable. Nevertheless, Gupta and Huefner found that cross-sectional differences in many financial ratios were primarily related to industry characteristics.

Elton and Gruber [1971] applied a cluster algorithm to the raw ratio data so as to improve forecasting through the design of homogeneous groups. In order to reduce the influence on the distance measure, they employed principal components analysis to produce a standardised set of criterion for each company. They found that ten pseudo-industries emerged, different from the SIC to industry classifications. However, clustering by pseudo-industry provided better forecasts of a company's earnings per share than that of the SIC. Another study by Falk and Heintz [1975] demonstrated a technique for scaling industries according to degree of risk. They found that the scaling is based on particular industry characteristics as measured by industry financial ratios.

All of the studies discussed above appear to be conflicting. Some studies, for example, like Brown and Ball [1967], Williams and Goodman [1971], and Gupta and Huefner [1972], seem to support SIC schemes. Wippern [1966], Gonedes [1969], and Sudarsanam and Taffler [1985] acknowledge that there are significant heterogeneous variances between companies in different standard groupings. If financial ratios are used as a tool for analyzing company performance, then it is valid to examine inter- and intra-industry differences among ratios. On the other hand, it is not appropriate to use financial ratios as a means of grouping companies, and then claim that the clusters thus produced were better than standard industrial classification schemes [Galitz, 1985, p. 451]. In particular, Gupta and Huefner [1972] described the instability of cluster analysis when the criterion variables changed over time across industries.

McDonald and Morris [1984, 1985] investigated the proportionality assumption that is implicit in ratio analysis for two samples of firms (1) an intra industry subset of 115 utilities and (2) a cross-industry sample of 120 US corporations. For the single industry, they found that the simple ratio model is robust with respect to the exclusion of an intercept term; that is, for the four ratios, (current assets / sales, current assets / current liabilities, total debt / total assets, and cash flow / total debt) investigated, the constant term is not found to be significant. However, for the heterogeneous group of firms analyzed, there was little consistency in the ability of any single ratio model. A more general model that included a number of remedial properties did not provide any significant improvement over the simple ratio method. Mcdonald and Morris [1984] cast some doubt on the usefulness of simple ratio analysis in cross-industry comparison, and thus one needs to control for industry differences.

In the opinion of Altman [1971, Reply p.1169] an analyst is advised to search for specific model when predicting results of individual firms. Ratio models dealing exclusively with firms in a particular industry or product line will yield more representative parameters which can be useful for future predictions of other firms in that same line of business. Related work on industry effects is found in studies by Buijink and Jerger [1986] and Lee [1985]. Both investigated the importance of size and sector effects, in the context of distributional properties of financial ratios. Buijink and Jegers have pointed to the importance of aggregate industry effects.

Mcleay and Fieldsend [1987] suggest inclusion of the sector and size effects in more generalized linear modelling of the relationship between two accounting variables. They show that the size and sector effects can vary considerably from one financial ratio to another. Lee [1985] certainly finds evidence of significant size and sector effects on ratio analysis. He suggests that the non-normality observed in financial ratio frequencies may be due to important systematic effects which render the data non-homogeneous. Lee [1985] has found some improvement in normal approximation, although normality is still rejected.

It appears that the use of an industry norm by both practitioners and researchers is motivated in many financial analysis aspects rather than only in failure prediction ones. Basic questions, such as (1) 'does the developed failure prediction model have the requisite control of industry-wide factors in the analysis",(2) "what is the structural disparity between industries", (3) "what is the proper criterion to cluster different industries, (especially the conglomerate industry), into the appropriate industry", (4) "how can the control of industry-wide factors be best achieved", are not frequently addressed by authors in developing a class of stable failure prediction models. Consequently, the reported models appear to be in many cases inconsistent with the different studies at the cross-sectional level leading to instability problems.

Therefore, choice of the appropriate industry relative ratios for firms within a given industry to control for industry-wide factors is required to build a stable model, to allow direct comparison of companies, and to enable the examination of the stability of forecasting across industries. There are different alternative advantages and disadvantages between existing SIC and cluster technique methods. In this study, we selected industry relative ratios and the existing SIC code rather than cluster analysis to control for industry-wide factors and determine industry classification, in order to reduce the bias due to industry difference. This is because (1) the financial ratio in this study is not normally distributed (see section, 6.2 below), and (2) each of the failed and non-failed observations are properly identified and matched by SIC code already (see section 6.6.1 below).

4.3.2 Control For Industry-Wide Factors

It is commonly argued that changes in corporate earnings or rates of return and other financial concerns of firms are influenced by economic and industrial factors. For example, a quote from Amit and Livnat [1990, p. 88] stated "that Lucas [1981], Prescott et al [1983], and Zarnowitz [1985] found that

> "the service sector has the smallest fluctuations about a trend while the business fixed investment sector has the greatest. Moreover, businesses tend to peak at different times during economic cycles".

In this section, industry-wide factors are explicitly taken into account when analyzing the financial statements of individual firms. Gupta and Huefner [1972] found that cross-sectional differences in many financial ratios were primarily related to industry characteristics. There are conceptual and practical difficulties in controlling industry differences. At the conceptual level, there is a lack of adequate theoretical knowledge about the different impact of many economic variables on the same financial ratios, even for a given firm or industry. On the practical level, it is more difficult to gather sufficient data to control for economic variability.

If it is assumed that many of these uncontrollable economic factors, such as supply and demand structures, etc..., are relatively constant within industries, but vary substantially across industries, then an industry stratification using financial ratios provides a method of controlling for such factors. The ratios of each industry change over time according to common economic fluctuations. In practical ratio analysis, the ratio of an investigated firm is often compared with the industry mean or median ratios in order to control for industry effects. In failure prediction models, the control of industry effects is frequently achieved by paired matching samples. Another device to improve predictive ability or stable forecasting, is when the examined ratios are divided by industry relative ratios, as done by Horrigan [1966] in his industry difference analysis, and by Izan [1984] and Platt and Platt [1990] in their failure/distress prediction area.

4.3.3 Choice of An Appropriate Industry Norm.

An 'Industry Norm.' is a set of products which are reasonably homogeneous with respect to the end product. Many published sources provide examples of industry standard ratios, such as, Dun & Bradstreet's Key Business Ratios. The choice of an appropriate industry standard or index, on behalf of industry-wide factors, depends to a large extent on the cross-sectional distributional properties of independent variables and financial ratios.

In order to locate the position financial ratios of individual firms within industry distribution, an analyst has a choice of a variety of measures to act as a possible industry norm. Prior to considering the appropriate industry norm, it is important to stress that the objective of this study is not to enhance any particular measure.

Theories pertaining to use of financial ratios rarely specify the use of unique summary measures. The choice of industry norm is largely dependent on both the characteristics of the data set and the nature of the analysis or model in which the financial ratios are used. The choice of industry norm is to a large extend influenced by the cross-sectional properties of the financial ratios within the industry. That is, industry norms will depend upon how the financial ratios are distributed amongst firms in the industry.

Assuming that financial ratios are generated as continuous random variables they could be described by any number of distribution forms: for example, the normal, the gamma, the student's t, the exponential or the log-normal distribution. Of these the normal distribution has been the most popular device by researchers. There are many advantages when dealing with a normally distributed variable and assuming normality aids the use of a variety of statistical testing procedures. For normal distribution, the mean and standard deviations represent a relatively meaningful criterion measure with which to locate financial ratios in terms each other. However, the empirical evidence is that most financial ratios are unlikely to be normally distributed but are in fact skewed [Barnes, 1982].

An alternative strategy to deal with non-normal distributions has been to accept the non-normality and search for alternative models which provide a better fit [Mcleay, 1986]. Deakin [1976] reported that the problem of skewed distributions of financial ratios could be overcome by a log-normal transformation. This would imply that the unadjusted financial ratio follows a log-normal distribution for which it has been the shown that the geometric mean, which is equal to the median for the log-normal, represents an optimal measures of central tendency. The use of the log-normal distribution is supported by the fact that the multiplicative central limit theorem states that the distribution of products and quotients, or ratios, of positive random variables tend to log-normality.

A study by Mcleay [1986] attempted to show the potential of the student's t distribution to approximate distributions of financial ratios. That is, Mcleay argued that since financial ratios exhibit greater density in the tails than found in the normal distribution, the student's t may represent a better fitting model. As a result, Mcleay goes on to argue that in the commercial application of inter-firm comparison, it can be seen that not only the mean but also the median and other descriptive statistics serve as comparative performance indicators. In fact, the chosen measures of location by Mcleay in his study coincides with a weighted mean conception.

Lev and Sunder [1979] examine what the suitable industry norm would be if the two financial variables which form the ratio are either both normally or both log-normally distributed. In the normally distributed case, it is found that the equally-weighted mean would represent a unstable measure since it does not conerge as the number of observations increases. It is found that the weighted mean, using total assets or equity as the weighting factor, coincides with the maximum likelihood estimator of the ratio of population means of the two financial variables. Accordingly, for normally distributed variables, the use of ratio of sample means, namely the weighted mean, seems more appropriate than the mean of the ratios (the equally weighted mean) as a summary measure for the cross-sectional ratio distribution. For the log-normally distributed case where both variables are log-normally distributed, the use of the geometric mean or median is advocated.

If the ratio is formed of two normally distributed variables, y and x, the equally-weighted mean of the sample ratios is below.

$$(1/n) \sum_{i=1}^{n} (y_i / x_i) \qquad (3\text{-}1)$$

Where :

n = the number of sample firms in the industry,

y_i and x_i = the distribution of ratio.

Furthermore, the larger the coefficient of variation for the denominator, x_i, the more serious is the problem of instability. The weighted mean of sample ratios, with the denominator used as the weighting factor [Lev and Sunder, 1979, p. 204].

$$\bar{y} / \bar{x} = \sum_{i=1}^{n} [(y_i / x_i)(x_i / \sum x_i)] \qquad (3\text{-}2)$$

The choice of industry norm could also shown that the coefficients from cross-sectional regressions can themselves be regarded as candidates for industry standards in certain cases. More precisely, if the relationship between x and y, the two components of the financial ratio, is approximately linear, homogeneous but not exact, it can be represented as

$$y_i = \beta x_i + \varepsilon_i, \quad i = 1,...n \qquad (3\text{-}3)$$

Where β is the industry norm and the residuals ε_i reflect the effects of factors unique to the firm. The least squares estimator of the regression coefficients, b, is given by

$$b = \sum_i x_i y_i / \sum x_i^2 = \sum_i (y_i / x_i) (x_i^2 / \sum_i x_i^2) \qquad (3\text{-}4)$$

In other words, if the assumption of constant error variance of ε_i is satisfied (i.e.no heteroscedasticity), then the weighted version above of the sample means provides an unbiased, consistent and efficient estimate of the industry norm, β. The weights (x_i^2 / $\sum x_i^2$) are only a special cases corresponding to the situation where ε_i is constant across all firms. In general an efficient estimator of the industry standard β is found by the weighted mean of the individual firms where the weights used are $(x_i / s_i)^2 / \sum$

$(x_i/s_i)^2$ when the standard deviation of the firm-specific factor ε_i is proportional to s_i. To explain, two special cases are considered:

1. when $s_i = x_i^{1/2}$; the optimal estimate of β is found by employing the weights $x_i / \Sigma x_i$.

   $b_i = \Sigma\ (x_i / \Sigma x_i)\ (y_i / x_i)$

   $= \bar{y} / \bar{x}$.

2. when $s_i = x_i$, the optimal estimates of β is found by employing the equally-weighted mean of firm ratios.

   $b_2 = 1 / n\ \ \Sigma\ (y_i / x_i)$

Thus, different weighting schemes of the industry ratio distribution are also consistent with different remedies for heteroscedasticity [Lev and Sunder, 1979].

Lev [1969] hypothesized that firms attempt to adjust their financial ratios to conform to their industry-wide averages. He required that (1) firms belong to an industry consisting of at least 10 firms, and (2) a full 20 years' financial data be available. The requirement which restricts the sample to large industries was imposed so that the industry mean would not be sensitive to the individual ratios which are used to compute that mean. In the case of large industries, the effect of any firms's ratio on the mean is negligible. The first requirement was set because least-squares regressions are applied in his study to each individual firm. Lev tried to extend his study in several directions:

1. Improvement of the model: His model is adjusted to the industry mean of the ratio according to the target ratio. As a result of the modified model, the median R^2 for the quick ratio increased from 0.2 to 0.4 and about 85% of the β coefficients were found to be statistically significant. In general, the

coefficients may change over time, reflecting the different economic conditions.

2. In developing a general model describing the behaviour of financial ratios, Lev expected the industry mean would be an important variable in adjusting the ratio, as well as assisting in financial ratio prediction. Specifically, a model which attempts to predict the level of a ratio should include the recent industry mean and a lagged variable of the ratio among the independent variables.

Lev's study implies that management are able to adjust their financial ratios over time in order to move towards the industry average. He suggests this could be achieved in two ways:

1. One way management can adjust the financial ratios to predetermined targets is too choose from the set of generally accepted accounting measurement rules (e.g., inventory valuation methods) those which affect the financial ratios in the desired direction.

2. Second way managers can include the desired ratios in their budgets and then regulate business operations such that the resultant ratios will conform with the budgeted ones.

Lev, however, does not explicitly state what technique or combination of these techniques are used to achieve adjustment towards the industry mean. This fact is reflected in Lev's choice of a partial adjustment model to test for the dynamic properties of the financial ratios in the 245 firms empirical study. Lev defined his model as follows:

$$\text{Log } Y_{k,t} - \log Y_{k,t-1} = \alpha + \beta(\log X_{k,t-1} - \log Y_{k,t-1}) + \mu_t$$

Where

$Y_{k,t}$ = the firm's financial ratio K for the year t,

$Y_{k,t-1}$ = the firm's financial ratio K for the year t-1,

$X_{k,t-1}$ = the industry mean of the ratio K for the year t-1,

t(year) = 1,...,20 K (financial ratios) = 1,...,6.

The β value determine the speed of adjustment. If the estimated value of β is found to be between 0 and 1, individual firms' financial ratios do adjust to the industry mean. The closer the β value is to 1, the greater the period adjustment. Lev's study estimated the partial adjustment coefficient and found that less than 10% of observations implied that firm's financial ratio do not adjust periodically to the industry mean.

4.3.4 Development of A Class of Stable Industry Relative Ratio Models

Many of the previous studies have presented impressive results to discriminate between failed and non-failed firms since Beaver's [1966] univariate model. However, these ex-post equations have not proved successful in forecasting which going concern firms will fail in the subsequent period. A major factor may be the influence of general economic conditions and an unstationary conditions over time and across industries.

Johnson [1971] reported that "ratios to predict failure....do not contain information about the intervening economic conditions...the riskiness of a given value for ratio changes with the business cycles". Taffler [1981] is even more explicit that "dramatic changes in the UK economy and major changes in the system of company taxation call subsequent inter-temporal validity into question." Most of the methodologies mentioned above have concerned certain statistical problems and benefited a variety of interested parties. For example, the former, statistical methods reporting ex-post (within-sample) classification results one year prior to failure are fairly consistent with respect to methodology, but not to the future ex-ante sample or the succeeding time period. In the latter case, investors may seek to avoid losses associated with failure. Although the ex post sample classification is generally satisfactory the hold-out sample is not.

Edmister [1972] used the industry relative variables calculated by Robert Morris Associates' (RMA) Annual Statement studies. He used industry average ratios and three years trend of each ratio, as well as a three year average of each ratio, as predictors for small business failure prediction. Five of the seven variables employing industry averages are tested. He concluded that the RMA averages are helpful in the prediction of small business failure, and the construction of Small Business Administration (SBA) average seems to offer little advantage.

Dambolena and Khoury [1980] used the concept of stability with a much larger set of financial ratios over time as independent variables in the derivation of a discriminant function to improve predictive ability. They found that they used Altman's latest model [1977] predicted better results than Altman's earlier model. This is because Altman addresses only marginally the question of ratio stability, and as such the treatment is far from adequate. They intended to employ ratio stability to correct Altman's model. 23 failed and 23 non-failed firms were drawn from the Dun and Bradstreet' Million Dollar Directory paired by (SIC) industry during 1969-1975 for the 8 years prior to failure.

They emphasize that data instability is greatest for firms about to fail and the unstable ratio has a significant increase over time as the firms approached failure. They developed two versions of discriminant functions for failure prediction. One version was derived from the stepwise procedure in choosing the significant variable from among 19 popular financial variables. The second version was measured by :

1. The standard deviation of the financial ratios over the three-years periods.

1. The standard deviation of the financial ratios over the three-years periods,
2. Their standard error of estimate around a 4 year linear trend, and
3. Their coefficient of variation over four-year periods.

Results from a stepwise selection of the best discriminators from among the same 19 ratios as well as the standard deviations of each of the ratios over a four year period showed that in most trials the model that included standard deviation data was significantly superior to the ratio-only model in prediction accuracy. The resulting discriminant function has a 94%, 80%, and 70% degree of classification accuracy during the first, three, and five years prior to failure compared to the 96%, 89%, and 83% classification accuracy when the standard deviation of ratios over time were added. The validation test for years 1, 3, and 5 were 87%, 85% and 78% respectively. They concluded that the models that used standard deviation data were slightly superior to the ratio only models for prediction one year prior to failure and substantially superior for predictions three and five years before failure. The difference between the estimation analysis and validation analysis was 9 per cent in the first year prior to failure. However, whilst there were improvements in ex-post classification results, there was no improvement in ex-ante classification accuracy.

Altman and Izan [1984] and Izan [1984] used the median as the industry norm to control for industry variation within their sample of Australian companies and demonstrated stable classification results ex-post and ex-ante. It is interesting to note that the median ratio distribution is used as standard for ratio evaluation. The reasons given for this choice of the median are generally related to its robustness to large outliers and measurement errors in a specific industry. Izan [1984] developed a corporate failure prediction model in Australia. The sample size used was the largest of any studies carried out in Australia, of a traditional financial ratio analysis and industry relative approach, taking into account differences across industries. The 50 non-failed sample was matched to the 53 failed sample by randomly selecting firms from the same industry for the same year using linear discriminant analysis. The sample of failed firms that had gone into receivership and liquidation came from the period 1963-1979. The date of failure is either the date the receiver / liquidator was appointed or the date of deleting from the Sydney Stock Exchange, whichever was earlier. Industry median data from the year of 1965-1979 were calculated. Izan suggests that

> "It is necessary to match exactly the industry median data to the year of sample since there is some variability of ratios over time".

The failed firms represent 12 industrial sectors and size ranged between $0.3 million and $143.0 million in tangible assets. He used the industry relative ratios to replace the traditional raw ratios in order to avoid the impact of industry differences since raw ratios can lead to significant industry sensitivity. He commented that the reason for this attempt to standardise by industry is the heterogeneous nature of the failed firms. The approach involves adjusting a company's raw ratio by dividing it by the appropriate industry median as follows:

$$X_{it} \;/\; X_{igt} \quad = \quad IR_{it}$$

Where

X_i = ratio i,

g = industry g,

t = year t, where t = 1975-1986, and

X_{igt} = industry g's median for ratio i in period t.

IR_{it} = Industry relative for ratio i in period t.

According to his investigation, an industry relative below 1.0 indicates a less than industry average performance for that ratio in that specific year. An industry relative greater than 1.0 indicates above average performance. It may be argued that a company's relative performance to its industry average might be distorted if the entire company is in a financial distress. This would imply that a company in a distressed industry may have a high industry relative compared to a lower relative of a company in a strong industry. Izan then built a linear discriminant model applying industry relative ratios one year prior to failure. Five industry relative variables yield a Z-score model based on the following: (1) X_1 = EBIT / Tangible Total Assets. (2) X_2 = EBIT / Interest Payments. (3) X_3 = Current Assets/Current Liabilities. (4) X_4 = Funded Debt (borrowings) / Shareholder Funds. (5) X_5 = Market Value of Equity / Total Liabilities.

The classification matrix using industry relative (median) ratios is 94.1% (48 of 51 correctly classified) for the type I accuracy and the 89.6% (43 of 48) for the type II accuracy. The overall accuracy is 91.9%. The model's accuracy is extremely good based on one year prior to failure, 82 per cent, moderately good based on two year prior to failure, 75.5 per cent, and less accurate in more remote years. In comparison with the original sample of classification accuracy, the adjusted industry relative (median) ratios appear to have only a mildly improved predictive ability over raw ratios for first year prior to failure. He concluded that his model could have been improved with a different set of variables but the likelihood of much improvement is quite small. As indicated earlier, the industry relative (median) approach has the additional advantage of being applied over a broad cross-section of industrial sectors. Izan claimed that his approach made the model universally applicable, but in the end his classification accuracy was only marginally better than the unadjusted model. His attention to differences between industries is worth consideration.

Betts and Belhoul [1987] study followed Dambolena and Khoury [1980] procedures to include the financial stability concept in the framework of the discriminant model to identify bankruptcies which improved the ability to distinguish between failed and non-failed firms. A sample of 39 failed firms in the first year prior to failure, 36 in the second, and 31 in the third, were selected. The 93 going-concern non-failed firms were randomly selected and not matched by size, industry, or financial year during

1974 to 1978. 29 financial ratios were selected on the basis of their popularity in the financial literature and their ability to discriminate between failed and non-failed companies in previous studies. To further determine the predictive ability of stability measures, Betts and Belhoul [1987] used the function result from ex post sample to validate the ex-ante sample which comprised 98 going-concerns selected at random and 17 failed firms. The validation method used was the leave one out method. The results were estimated up to five years prior to failure for the failed firms. The correct classification rates indicate that the predictive power performed less well and showed a sharp decline in their ability to classify the validation sample set in years other than one year prior to failure. They also test all the assumptions of discriminant analysis. However, the prior probability and mis-classification cost should have been taken into consideration. Several comments are suggested by them in the following:

1. Adjust the ratio data for each company depending on the state of industry and economic cycles. Ratios in each industry differ markedly from one industry to another. It would be better to adjust each ratio based on different industry characteristics to the normative standpoints.

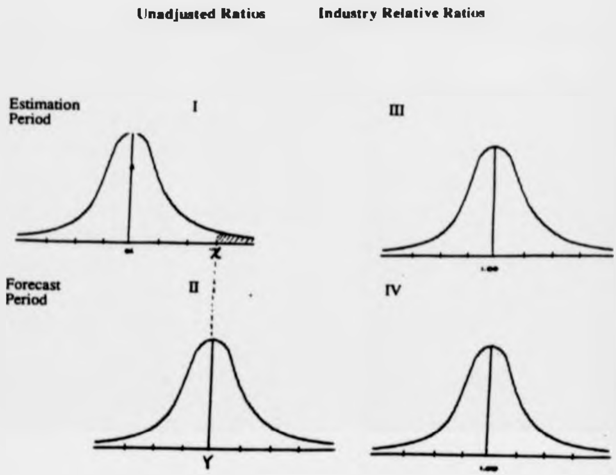
2. Adjusted ratios reveal a company's relative performance in its industry, relative to other firms in the same year, relative to other firms in the same industry and relative to other firms in the heterogeneous industry. These enable valid intra-industry and inter-industry comparison to be made across industries and are shown to be more stable than unadjusted ratios.

3. Many financial services report average or median financial ratios of firms within industries, presumably to facilitate intra-industry comparison.

To illustrate such time series shifts in the behaviour of financial ratios, consider the shift in distribution of the financial ratio illustrated in Figure 4.1. In the estimation period, (I), the ratio distribution is centred around a whilst observations to the right of a point like X would represent a relatively large value. Assuming that the distribution for this same ratio has shifted over time such that in the forecast period, diagram (II), the distribution is now centred around Y. Notice now that the mean of the forecast distribution, Y, is equal to the X value in diagram (I). If the former ratio distribution was used as an estimation period (1980) for a model which was subsequently tested on the forecast sample, some considerable errors in the forecast period (1985) would be expected.

However, as noted above, financial ratios may change across time for a variety of reasons. An industry relative ratio incorporates both the individual company's response to an event as well as the industry response. One attractive feature of this formulation is that it allows for changes to occur over time, yet it forces the expected value of the distribution of the industry to remain fixed at 1, assuming that variance is constant. Thus, an industry relative variables should ameliorate the data instability problem, and still allow for changes within an industry. Figure 4-1 shows that the industry relative ratio model appears to be more stable and efficient forecast than a model using unadjusted ratio.

Figure 4.1 Comparison of Unadjusted and Industry Relative Ratios and Their Stability Over Time



In this thesis, we made great effort to maximise our sample size of failed companies so as to examine a number of different hypotheses in this study (see chapter 1). These samples come from different industries with different financial characteristics, so it would be better to develop a stable model and examine its forecast ability by utilizing the industry relative approach as suggested by Altman and Izan [1984], Izan [1984], Foster [1986], and Platt and Platt [1990]. Platt and Platt [1990] used the mean ratios in the firm's industry as industry-wide factor. Unfortunately, Altman and Izan [1984] and Platt and Platt's [1990] studies employed the industry relative ratios both from the Sydney Stock Exchange Ltd and the American Internal Revenue Service [IRS] **official reports respectively, rather than industry relative (mean or median) ratios produced from individual firms**, with no data supplied on how the official statistics are computed. In this study, industry relative ratios **produced from each individual firm** rather than **official reports** is applied.

4.5 Alternative Methods to Estimate Industry Relative Ratios

An alternative approach is to control for the hypothesized source of heterogeneity across industries over time when estimating values of the independent variables of each company. Consider the use of industry relative ratios as a choice of controlling for differences across industries over time in their average financial ratios. Some technical issues in computing industry relative are worth considering. Should it be the industry mean or industry median ratio in the industry? Computation of the industry mean and median are discussed as follows.

4.5.1 The Procedure of Producing Each Sector's Industry Mean Ratios

If the industry mean is chosen as the norm, should it be an equally weighted mean of all firms' ratios or a value-weighted mean?

Table 4-1 illustrates the computation of equal- and value- weighted industry net income to total sales ratios (For example, R1, Net Income / Total Sale, in this study), calculated as followed:

(A) The equal-weighted industry average for 1975 year is

$$1/4\ (20\% + 15\% + 13\% + 12\%) = 15\%$$

The equal-weighted industry average for 1976 year is

$$1/4\ (25\% + 17\% + 15\% + 14\%) = 18\%$$

(B) Computation of a value-weighted index requires choice of a weighting scheme.

1. Weighted by the total sale for the 1975 year (denominator of ratio):

(£200 / £1000) x (£1000 / £10000) + (£300 / £2000) x (£2000 / £10000) +

(£400 / £3000) x (£3000 / £10000) + (£500 / £4000) x (£4000 / £10000)

= (£200 + £300 + £400 + £500) / (£10000)

= 14%

2. Weighted by the total sale for the 1976 year (denominator of ratio):

(£300 / £1200) x (£1200 / £10800) + (£400 / £2300) x (£2300 / £10800) +

(£500 / £3200) x (£3200 / £10800) + (£600 / £4100) x (£4100 / £10800)

= (£300 + £400 + £500 + £600) / (£10800)

= £16.6%

Table 4-1 Computation of Equal and Value Weighted Industry Average Ratio

	Firm1	Firm2	Firm3	Firm4
Year 1975, Textile sector				
Net Income	£200	£300	£400	$500
Total Sale	£1000	£2000	£3000	£4000
NI/TS	20%	15%	13%	12%
Year 1976, Textile sector				
Net Income	£300	£400	£500	$600
Total Sale	£1200	£2300	£3200	£4100
NI/TS	25%	17%	15%	14%

Source: This study

Industry mean ratios in this study were calculated by including all firms with data available each year in the population from Datastream. Any surviving companies in the specific year (for example, 1975 or 1976 year) for each sector can be included as a aim in this study. Forty-one industry relative financial ratios in each of sixteen sectors are derived from the weighted average ratios of the firms reporting to DATASTREAM. The procedures of arriving at each sector's equal weighted industry mean ratio are below:

1. The identification of each failed and non-failed firm's sector according to International Stock Exchange Year Book, Financial Times, and EXTEL card.

2. The formulation of 41 financial ratios based upon the equation we developed in the DATASTREAM computer program.

3. The calculation of the first financial ratio for each firm in the industry adjustment group and the second financial ratio for each firm in the industry sector, up to 41 selected financial ratios.

4. The calculation of each industry average ratios based on all surviving firms listed in an DATASTREAM industry for each year represented.

5. The repetition of procedure 3 for the other 15 industry sectors.

6. The addition of the first financial ratios of each firm in a sector and then division by all firms in this sector, for all 41 ratio investigated.

7. The repetition of procedure 5 for each sector and for a 15 years period

The above process is repeated for each of the surviving firms included from 1971 to 1985 , a 15 year time span. For example, for firms that failed in 1975, we selected the 1971-1975 year period for a 5 year time span to calculate the industry mean ratio at once; if firms failed in 1985, the time period covered will be 1981-1985, and so on because DATASTREAM can only provide five years data once. Foster [1986] suggests that if an analyst wishes to use an equal- or value weighted index as a summary measures, the index can be markedly affected by extreme values of ratios. Extreme values of ratios can occur when computing ratios for firms and it is important to plot the individual observation, at least to be aware if extreme values do occur in the sample. The computer program for selecting the industry mean ratios is given in Appendix C

4.5.2 The Procedure of Producing Each Sector's Industry Median Ratios.

Industry median is found by ranking ratios from lowest (highest) to highest (lowest) and choosing the middle ratio. The median ratio is used as the measure of central tendency in both Robert Morris Associates' Annual Statement Studies and Dun & Bradstreet's Key Business Ratios [Foster, 1978]. In order to minimize the distortion to the industry mean ratio that might be induced by one or two extreme observations in a specific industry, or if the entire industry is in a financial distress situation, the industry median ratio is selected instead of the industry mean ratio. For example, assume that an analyst is examining net income to total sale ratio in the textile industry. Data for the total nine publicly listed DATASTREAM companies in 1975 are:

Firms No.	Firms Name	NI/TS	Net Income (NI)	Total Sale (TS)
128	DUNHILL HOLD	10%	£100	£1000
129	FARNELL ELECT.	11%	200	2200
130	GENERAL ELECTRIC	11.8%	2500	29500
131	GUINNESS	12%	2700	32400
132	HOWDEN GROUP	*13%	3000	39000
133	JONES,STROUD	15%	200	3000
134	A.B. ELECTR	16%	250	4000
135	C.H. BAILEY	17%	80	1360
136	BEATSON CLARK	19%	240	4560

The median ratio is 13%, avoiding the effect of extreme observations present in the sample. Due to lack of industry median data on the relevant statistical data base and other information, we compile the industry median figures using the formulas or data available in the DATASTREAM's financial statement. Industry median data from the years 1974 to 1985 were compiled. This was based on the DATASTREAM's Standard Industrial Classification [SIC] in which companies are grouped into sixteen sectors. The procedure to produce selected industry median ratios for 16 sectors is given as follows:

1. The repeation of procedures 1, 2, 3, in above the procedure of industry mean ratios [see 4-5-1]

2. The sort of each financial ratio in descending order by ranking ratios from lowest to highest and choosing the medium ratio for each financial ratio in every sector,

3. The repeation of procedure 2 for the other forty-one financial ratios,

4. The repeation of procedure 2 and 3 for the other 16 sectors, and

5. The repeation of procedure 2, 3, 4, over the 15 year period from 1971 to 1985 for each year of sample data because of the expected variability of ratios over time.

Foster [1986] states that one of the benefits in selecting median ratios is that "the analyst can select those few firms that are considered of special interest (for example, due to size similarities)". Izan [1984] suggests that the industry median is selected rather than the average in the industry-relative calculations because one or two outlier firms in a specific industry could distort the measure of central tendency if the average ratio was utilised, especially if the industry has relatively few members (e.g., some specific industries).

In this study, both industry mean ratios and industry median ratios are all applied in examining the stability of forecasting failure prediction models. The empirical result will introduced in chapter 7 and 8. Nevertheless, we found the forecasting between ex post sample and ex post sample is more stable in terms of classification rate when the use of industry mean ratios rather than the industry median ratios. (see chapter 7-8). The computer program for selecting the median figure is given in appendix D. Industry mean and median ratios for each sector are presented in Appendix E and F respectively.

4.6 Developing A Specific Industry Model

In bankruptcy prediction models, analysts should understand a different financial characteristic for each sector. One possibility to cope with this heterogeneous problem across industries is to build separate discriminant models for each specific industry in which failure occurs. While this approach does control for industry differences in financial ratios, in many cases it will lack enough data for each particular industry, especially in the problem "failure" companies or "sector" categories. Recognizing this, Van Horne [1974] suggested that similar companies comparisons can be made by using companies that are in the same industry. A number of authors have focused their failure prediction efforts on a specific industry. For example, Altman [1973] on railroad specific industry, Mason and Harris [1979] on the construction industry, and Meyer and Pifer [1970]; Sinkey [1975]; Pantalone and Platt, [1987b]; and Korobow, et al.,[1976] all on commercial banks, Altman and Lorris [1976] on brokers and dealers; Pantalone and Platt, [1987a]; and Barth et al., [1985] on thrift failure, Collins [1980] on credit unions.

Mason and Harris [1979] develop a model specifically focusing on the construction industry. It was concerned with two sets of financial ratios that were used in the UK database. The first set was derived from the final year's accounts of 20 continuing companies that were thought to be particularly sound based on the traditional financial ratio analysis from the 1976-1977 accounts. 20 failed construction firms were derived from the receivership, voluntary or compulsory liquidation, or having received government assistance between 1969 and 1978. A list of 28 initial financial ratios were used, and were reduced to a small number to distinguish failed from non-failed firms. Six financial variable models were produced by the following discriminant function:

$$Z = 25.4 - 51.2R1 + 87.8R2 - 4.8R3 - 14.5R4 - 9.1R5 - 4.5R6$$

Where

R1 = Profit Before Interest and Tax / Opening Balance Sheet Net Assets
R2 = Profit Before Interest and Tax / Opening Sheet Net Capital Employed
R3 = Debtors / Creditors
R4 = Current Liabilities / Current Assets
R5 = Log10 (days debtors), and
R6 = Creditors Trend Measurement

Six financial ratios included five clear aspects of financial attributes. They conclude that since R2 and R5 appear important discriminators and R3 and R6 add relatively little, short-term liquidity is less significant than more essential aspects of a firm's structure. The correlation between the two profitability measures (R1 & R2) is 0.92, but because of multicollinearity, it is not possible to identify the relative contributions of each of the ratios to the power of the model. The success rate of the model is 100%, with no mis-classification, but a further eleven failed firms were used as a test group and their classifications resulted in type I errors in a validation sample. The per centage of the total 31 failed firms was 87%, 68%, 55%, and 58 percent first year to fourth years prior to failure. Taffler [1980, 1984] states that Mason and Harris were the first two people in the UK to focus on the specific construction industry. Their model is of interest both to the potential user and the theorist.

Storey et al [1987] also found that the accuracy of failure prediction for their small firms could be improved by developing models for specific industries. All of the researchers described above attempted to restrict their data sample to a single industry to eliminate the problems of inter-industry differences. Platt and Platt [1990] state that focusing on one industry is analogous to using industry relative ratios in samples including several industries since the relative position of firms within the industry is reflected by the relative position of any given financial ratio. In this study, one of our objectives will be to examine how much the model can be improved by an industry specific model or an aggregate model. The result will be presented in chapter 9.

4.7 Summary and Conclusions

There are many different reasons why the model may not be stable over time and across industries. Many previous researchers have endeavoured to use alternative methods to solve the instability problems. Mensah [1984] considered business cycles to cope with the macro-economic influence. Izan [1984] and Platt and Platt [1990] used industry relative ratios to deal with the instability problems. Altman [1973] and Manson and Harris [1979] estimated industry specific models. However, these studies described above have considered industry and economic impact respectively. None of them considered industry and economic difference simultaneously in developing and forecasting failure prediction models. This study will focus on the following empirical objectives:

1. Comparison of the predictive ability between industry relative ratios and unadjusted ratios (chapter 7),

2. Development of three different stable models considering industry and economic influences simultaneously, (chapter 8)

3. Comparison of each industry specific model with the aggregate model (chapter 9),

4. Examination of the stability of forecasting for each of the different models (chapter 7, 8, and 9).

Hopefully, these methods described above can cope with the instability problem of failure/distress prediction models.

Chapter 5: Research Methodology

5.1 Introduction

The purpose of this chapter is to explain and illustrate the general nature of multiple discriminant analysis. It also provides a basis for the interpretation of the results of the study. The chapter begins with a research design and sample selection, followed by a general overview of discriminant analysis. An important issue discussed is evaluating the significance of independent variables and incorporating prior probabilities and misclassification costs. The problems, and the steps involved in using discriminant analysis are also reviewed. The procedure for testing the predicting ability of the discriminant function, and a discussion of its robustness is also presented as follows.

5.2 Research Design

Kerlinger [1973, p. 300] suggested that research design has two basic purposes: (1) to provide answers to research questions, and (2) to control the maximization of experimental, extraneous variables, and the minimisation of error variances of the problem under study. Research designs are invented to enable the researcher to answer research questions as validly, objectively, accurately, and economically as possible. This study's research plan is deliberately and specifically conceived and executed to bring empirical evidence to bear on the research problem.

5.2.1. Sample Design

1. The sample in this study is derived from a population of two groups: (1) the experimental group - failed group; (2) the control group - non failed group.

2. To avoid the effect of extraneous variance, we limit the sample to UK firms. The criterion was imposed so as to maintain sample homogeneity by ruling out economic, political, social, law, institutional and cultural causes of corporate failure irrelevant to the UK. The results will be restricted to the UK.

3. In order to further avoid the effect of the extraneous variance, the matching of the sample was based on three criteria, (1) same industry, (2) the corresponding year, and (3) similar levels of total assets employed. The purpose is to control some confounding influences by matching the failed firms with non-failing firms according to industry, size and economic-wide factors.

5.2.2 Selection of the Failed Firms.

The most difficult task of data collection was finding a sample of failed firms for which financial statements could be obtained. In this study, the failed firms were identified from the Stock Exchange Official Year-Book (SEOYB) which provided a list of companies in liquidation and receivership with entries in company section. Either the liquidator or receiver of the companies will be removed from the Register under the provisions of Section 653 and 427 of the Companies Act, 1985 (see: SEOYB, 1989, P.1068). The sample of failed firms includes all those in the Datastream's which had failed during the period 1974 to 1985 (inclusive). The date of failure is defined by the last financial statements prior to failure and satisfy the following conditions:

1. Be a UK industrial firm according to Standard Industrial Classification (SIC) and was listed on the International Stock Exchange Official Year Book.

2. Financial ratios based on each firm's account items were available from the Datastream database for the 5 years prior to failure for failed firms and a

corresponding 5 year period for each non-failed firm (a minimum of one year and a maximum of five years reported).

The total of failed firms which met the above conditions was 88. The set of failed firms are presented at Appendix H. Concerning (1) (see section 5.2.1), and (2) the second criterion was imposed because it was intended to perform the analysis for each of the five years before failure. The time period also available up to 1985 fiscal year. Of a 12 year time span was considered long enough to reflect the changes in the general economic condition. The number of companies which failed within each of these years is sufficient to allow for a study of failure at different phases of the business cycle. The selection criterion excludes commodity groups (utilities, mining, finance), financial groups (banks, discount houses, insurance, property, investment trusts, etc) and overseas, trade companies. These selection reflects Ohlson [1980] observation in the US context that, "companies in these industries are structurally different, have a different bankruptcy environment, and appropriate data are, in some cases, difficult to obtain".

One problem in this study was that the failed firm sample was concentrated in a few industries which are difficult to match with the approximate non-failed firms. For example, in the early 1980's the toy industry in the UK was decimated [Keasey and Watson, 1991] and there are insufficient survivors to match with. Textile, non-failed firms which faced financial insolvency but continued in operation are also included. Thus, the accuracy of classification between healthy and at risk non-failed firms when matched with failed firms will have more or less different results. It is possible that the failure prediction model developed from data for that period will be somewhat biased by an industry effect.

5.2.3 Selection of Non-Failed Firms

Ideally, the control sample should be a random sample of non-failed firms with data covering the corresponding years as the failed sample. In practice, many researchers employ non-random samples because of a variety of reasons [see Keasey and Watson, 1991 and section 3.4.5]. However, Palepu [1986] suggests that the use of non-random samples has three drawbacks that make the reported predictive results unreliable. In an empirical context Zmijewski [1984] found that, while non-random samples gave rises to biases, the biases did not appear to materially affect the overall classification rates. In fact the literature on choice-based sampling suggests that non-random sampling at the estimation stage can have positive benefit. A choice-based sample can often provide more precise estimates than random sampling for a given sample size.

However, Manski and Lerman [1977] state that using statistical tests on samples where the probability of selection varies for the failed and non-failed companies can result in biased estimates of the model's parameters and overstate the model's predictive ability. A frequent procedure is to control industry and size effect influences by matching the failed firms with non-failed firms. The sample used in this study was selected using a matched-pair approach. The financial statement data was collected according to year before failure. For example, if two firms failed in 1984 and 1980, respectively, and their latest financial statements were prepared on December 31, 1983 and 1979, respectively, the first year before failure would include the 1983 statements of the former and the 1979 statements of the latter. The financial statement data of the non-failed firms was also stratified into years before failure, corresponding to the years that were assigned to their failed firms. On account of financial statement data not being available for every year prior to failure, the number of observations decreases as the time period preceding failure increases. The sample numbers are the biggest in the first year prior to failure - 264 firms and the smallest in the fifth year - 260 firms (See: Table 5-3).

The matching procedure in this study is followed:

a. The first year before failure is defined by the last published financial statements prior to the date that the firm failed. Thus, companies might have been in business for different periods before failure. The second year before failure is the fiscal year before the first year and each of the years prior to the first and second year before failure are sequentially defined as the third, fourth, fifth before failure. The financial statements of the non-failed firms were acquired for the same fiscal years as those of failed firms.

b. Industry was selected as the most important criterion, and it proved difficult to define. DATASTREAM classify into level 3, level 4, and level 5 industries; a level 3 classification is the broadest definition of an industry, a level 5 classification is the narrowest definition. In this study, we select level 3 rather than level 4 and level 5 in an attempt to calculate a great number of industry relative ratios. Companies failing in prior years were allocated Standard Industry Classification on the basis of the classification of International Datastream. The 88 failed firms and 176 non-failed firms were operated in 16 different industries [see: Table 5-1]. The most frequently and enormously represented industry was textiles which consisted of 23 failed firms and 46 non-failed firms.

c. Size, measured by total assets of each firm used in the latest year's balance sheet prior to failure, was the next most important criterion. Within the same industry group, it was possible to select two firms whose asset sizes were closest to the asset size of the failed firm to be matched with data available in Datastream. This procedure matches failed firms with non-failed firms in the same industry, of approximately the same asset size.

The 88 failed firms cover 16 industrial sectors and ranged in size from the smallest 0.4 million pounds (chemical sector) to the largest 6.7 million pounds (transport sector) in total assets. The sample excluded finance and investment companies because of different economic characteristics and regulatory environment. In this study, the failed sample's asset size distribution contained mostly the medium and large size firms. Once a sample of bankrupt firms is obtained, a control sample of non-bankrupt companies must be drawn. Jones [1987] stated that:

> Bankrupt firms are often disproportionately small and concentrated in certain failing industries. If non-bankrupt firms were drawn at random, there would probably be substantial differences between the two groups in terms of size and industry. The result is that the model attempting to discriminate between failing and healthy firms may actually be distinguishing between large and small firms, or between railroads and other industrials.

In a study of furniture manufacturing in New Zealand, Lawrence [1982] finds that for meaningful comparisons of profitability, one has to control the size and location of the sample firms. He shows that even within a homogeneous industry, differences may be attributed to firm size and location. Thus, in this study, in order to alleviate the size effect of failed and non-failed firms, we made our best effort to control for the sample so that the classification of firms to industries will yield homogeneous characteristics in terms of industry effect. Because of the lack of sufficient information about company's location and age variables, neither of them will be considered in this study.

The selection of the non-failed companies is made in two stages. In the first stage, a large number of surviving companies are selected according to the following criterion:

1. The company is recorded as a continuing company for the last fiscal year to the date of failure in the DATASTREAM data base, which is the fiscal year to the date of failure.

2. The company has been listed for at least five years, for which the company's accounting data are available in the Datastream data base.

3. Two non-failed firms of the same industry and similar asset size were selected to match each failed firm. Because there are so many non-failed firms in the real world. Taffler [1982] used 23 failed firms and 45 non-failed firms as a case to construct a failure prediction model. The non-failed firms are presented at Appendix G.

The number of companies matched to those of the failed firms, 176, were selected from nearly 1300 Datastream companies by the same industry, corresponding year, and approximate total assets were found. The 264 firms in total in the sample comprising 88 failed firms and 176 non-failed firms. The industrial classification and grouping is given in Table 5.1. At a broad level of classification 3 industrial groups are identified: Contracting, General-Engineering, Textile, Other Manufacturing, and Miscellaneous.

5.2.4 Classification of the Sample

All samples in this study are classified into several sub-samples on the basis of the objective of research. They are classified into the following groups:

(1) Ex Ante and Ex Post Sample Size.

The model was developed using firms which failed during the period 1974-1981 (inclusive). The ex ante firms are those which failed during the period 1982-1985. 52

failed firms and 104 non-failed are assigned to ex post sample, and 36 failed and 72 non-failed firms during the period 1982-1985 are assigned to ex ante sample. In splitting the total sample into the ex post (analysis sample) and ex ante (hold out sample) parts, a balance was considered regarding the distribution by year of failure (see Table 5-2).

(2) Failed and Non-failed Firms in Each Year Prior to Failure

Table 5-3 show the sample size are available for each year prior to failure, due to data availability.

(3) Number of Companies in Each Business Cycles

The sample years are divided into three periods based on the degree of movement of three macro-economic variables (inflation rate, interest rate, and real GNP) [see Table 5-6]. 1974-1978 was the expansion period, 1979-1981 recession and 1982-1985 recovery.

Table 5-1 Industry Name and Sub-Groups

Datastream Industry	Code	Industry Name	Total	Failed	Non-Failed
1. 02	BLDNG	Building Materials	6	2	4
2. 03	CONTRA	Contracting	27	9	18
(1) Contracting Group			33	11	22
3. 07	ENGEN	Engineering	27	9	18
(2) General-Engineering Group			27	9	18
4. 35	TEXTL	Textiles Group	69	23	46
(3) Textile Group			69	23	46
5. 04	ELTCA	Electricals	6	2	4
6. 08	METFM	Metals & Metal	12	4	8
7. 09	MOTGP	Motors	15	5	10
8. 22	BRDIS	Brewers & Distil.	3	1	2
9. 25	FDMFG	Food Manufacturing	6	2	4
10 31	PKPAP	Packaging & Paper	6	2	4
11 42	CHMCL	Chemicals	9	3	6
12 43	CONGL	Conglomerates	3	1	2
(4) Other Manufacturing Group			60	20	40
13 32	MEDI	Media	12	4	8
14 34	STORE	Stores	12	4	8
15 44	TRNSP	Transport	6	2	4
16 48	MISCS	Miscellaneous	45	15	30
(5) Miscellaneous Group			75	25	50
Total			264	88	176

Table 5-2: Sample By Year of Failure

	Time	Failed	Non-failed	Total
Initial Sample	1974	2	4	6
(Ex Post Sample)	1975	3	6	9
	1976	2	4	6
	1977	3	6	9
	1978	5	10	15
	1979	6	12	18
	1980	18	36	54
	1981	13	26	39
Sub-Total		52	104	156
Hold-out Sample	1982	8	16	24
(Ex Ante Sample)	1983	15	30	45
	1984	9	18	27
	1985	4	8	12
Sub-Total		36	72	108

Table 5-3 Number of Failed and Non-failed firms for This Study Prior to Failure

Year Before Failure	1	2	3	4	5
Failed Firms	88	87	86	85	84
Non-failed Firms	176	176	176	176	176
Total Number	264	263	262	261	260

(4) Time Series Sample Classification:

Table 5-4 Time Series Sample Classification

Sample Companies	Failed	Non-failed	Time
Analysis Sample	52	104	1974-1981
Hold-Out Sample	36	72	1982-1985
Total	88	176	

(5) Sector Classification:

Table 5-5 Sector Sample Classification

Sector Groups	Failed	Non-failed	Total
Contracting	11	22	33
Engineering-General	9	18	27
Textile	23	46	69
Other Manufacturing	20	40	60
Miscellaneous	25	50	75
Total	88	176	264

(6) Business Cycles Period Classification:

Table 5-6 Sample for Business Cycles Period Classification

Business Cycles	Failed	NF	Total	Time
Expansion Period	15	30	45	1974-1978
Recession Period	37	74	111	1979-1981
Recovery Period	36	72	108	1982-1985
Total	88	176	264	

(7) Sample Size of Each Sectors

Table 5-7 Total Assets (TA) Five Years BF by Industry and Type of Company*

Industry Code Total Assets	Years One (TA)	Prior Two (TA)	To Three (TA)	Failure Four (TA)	Five(TA)
02 Building Materials					
Failure	15162	16191	15782	11816	9850
Survivors	14893	14911	12752	9200	7854
03 Contracting					
Failures	19283	22178	15857	12411	10578
Survivors	20733	18192	13957	11939	10376
04 Electricals					
Failures	8228	9352	9327	6512	4886
Survivors	8874	8119	7118	6430	5370
07 Engineering-General					
Failures	46160	53808	48620	53638	50551
Survivors	40881	38035	34016	31013	29074
08 Metals & Metal Forming					
Failures	10580	10714	12528	16820	16074
Survivors	14029	12601	11924	12873	12801
09 Motors					
Failures	18739	19375	15710	15402	13638
Survivors	18112	15425	15474	14327	13047
22 Brewers & Distillers					
Failures	12029	11631	12571	14014	11571
Survivors	19043	16012	16016	15329	12797
25 Food Manufacturing					
Failures	30866	32995	27276	22645	20555
Survivors	21171	16026	11530	9618	7946
31 Packaging & Paper					
Failures	21279	23046	24431	22257	15482
Survivors	26226	23644	21030	18478	16748
32 Media					
Failures	10519	14765	14624	13285	13010
Survivors	17092	14806	12151	9532	7143
34 Stores					
Failures	14431	15208	13568	11153	14858
Survivors	19109	16856	16210	12919	11441
35 Textiles					
Failures	11764	12447	11247	9502	8816
Survivors	15414	14380	12883	11419	10193
42 Chemicals					
Failures	5061	4900	4753	4379	3909
Survivors	14188	13416	12379	10132	8201
43 Conglomerates					
Failures	20041	20888	17980	14947	12938
Survivors	19849	17427	14824	13555	12415
44 Transport					
Failures	66704	72193	61102	56926	48819
Survivors	49688	45655	42726	39732	29100
48 Miscellaneous					
Failures	13480	16267	14115	11555	10572
Survivors	12752	12278	11147	9958	8741

*Companies were matched based on total assets one year prior to failure.

5.2.5 Selection of the Independent Variables

As we have discussed no convincing theoretical framework for bankruptcy prediction exists, and instead researchers weigh more heavily the demonstrated empirical evidence of usefulness in the choice of ratios.

In this study, we rely particularly heavily on prior literature on this issue. Forty-one ratios (excluding one ratio due to incomplete data) were selected for the group of failed and non-failed companies. The set of independent variables included in this study is nearly a comprehensive set of all possible variables. The variables are selected based on their frequent appearance in the literature, good performance and significance in predicting failure studies and popularity among Practicing accountants. The variables used in this study comprised 41 financial ratios chosen in order to reflect a broad range of important characteristics relating to the economic, financial and trade structure of industries. These ratios, together with the definitions of their components are listed in the Appendix A. For each of the failed firms and non-failed firms, the ratios were calculated using balance sheet, profit and loss accounts, and financing tables for five years prior to failure. Data was derived from DATASTREAM.

A difficulty which is typically encountered by analysts and researchers is whether or not financial statements should be adjusted to reflect differences in accounting methods and corporate policies. The position of analysts and researchers varies, on the one hand, from those who make adjustments to, on the other hand, those who do not. There have been a number of empirical tests of various types of inflation accounting, pertaining to samples of American or English firms. In the context of predicting business failure, Ketz [1978] and Norton and Smith [1979] tested general price level adjustments accounting, Mensah [1983] and Keasey and Watson [1986] evaluated current cost accounting. As a general observation inflation accounting was not found to be superior to historical cost accounting in these studies. However, when considering the impact of some adjustments they made on financial statements Dawson, Neupert and Stickney [1980] argued that with a few exceptions:

> "the benefits of adjusting net income and financial statement ratios for differences in accounting method hardly seem worth the effort".

Consequently, it was decided that the strategy followed by this study was not to make any adjustments to the financial data on the basis of any difference in accounting methods. Clearly the positive accounting research agenda has established that accounting policy choice varies systematically with a firm's contracting costs, and one might hypothesize that failing firms might chose accounting representations which might flatter their gearing, solvency, profitability ratios. The evidence of the bankruptcy prediction literature is that despite this bias accounting information is still effective.

5.2.5.1 Factor Analysis

Multicollinearity occurs when some of the variables are highly inter-correlated. The main problem is that when multicollinearity is present, the computed estimates of the regression coefficients are unstable and the interpretation of the role of the several attributes becomes very difficult. The problem was evident in the failure prediction study by Joy and Tallefson [1975, p.729]. They came to a similar conclusion. In the failure prediction area, factor analysis has been used by many authors, for example, Pinches and Mingo [1973]; Stevens [1973], Taffler [1982], and Mensah [1984]. The presence of multicollinearity can lead to disagreement between different measures of variable significance.

One simple way to test for multicollinearity is to examine the correlations among the variables. If, for example, two variables are highly correlated (say greater than 0.95, the critical value will be much lower with a large sample), then it may be simplest to use only one of them since one variable can convey essentially all of the information contained in the other. Altman and Eisenbeis [1978, p. 188] state that multicollinearity may affect the standard deviations of the coefficients when MDA is used. There are several reasons for the increasing popularity of factor analysis among researchers. Factor analysis appears to be an objective way to reduce the available data to a more manageable level. It is also effective in reducing the problems of multicollinearity and redundancy often associated with the use of large numbers of financial ratios. Moreover, in the absence of a well-established theory to guide the selection of variables in the context of a specific decision or event, factor analysis can be an expedient means of choosing variables.

In spite of these advantages, several issues exist in the use of factor analysis. There is no absolute guarantee that variables so selected necessarily represent all relevant dimensions of the subject are under study. Neither will all dimensions be equally represented. For example, when initial variables are selected by examining the literature, with additions and deletions made on the basis of the researcher's judgment, an important dimension will be included only if it is already in the literature or if the researcher is aware of it. However, because the financial ratios instability of failure companies, the overriding requirement in its usage is to bear its limitation in mind when interpretating the results of its use. In this study, we did factor analysis but did not use it due to instability under three different methods (Industry mean ratios (IRR1), industry median ratios (IRR2), and unadjusted ratios (UR)) for different comparative purposes (for example, three aggregate models, ex post models, three business cycle models for three IRR1, IRR2, and UR methods, five industry-specific models). Therefore, we performed a factor analysis on the ratios but did not use it in this study for ratio choice because of these reasons.

5.2.6 Definition of Groups and Ratios

Discriminant analysis procedures assume that the groups being investigated are discrete and identifiable [Eisenbeis, 1977]. That is, an observation cannot simultaneously belong to two or more groups, but it must belong to one of the groups under study. Eisenbeis [1977] argues that if the groups under investigation represent arbitrary segments of an inherently continuous variable, information is discarded concerning relationships between the descriptor variables and the grouping criterion variable. Moreover, error is introduced in the assessment of classification results since one cannot be certain of the proper population to which an observation should be assigned. In this study, it is considered that this will not be a problem since the two groups of companies analysed are clearly separated between failed and non-failed firms.

5.3 Data Analysis

5.3.1 Multiple Discriminant Analysis [MDA]

MDA techniques are used to classify observations into one or more alternative groups (populations) based on an analysis of selected characteristics believed to be related to group membership. These groups in this study are known to be either failed or non-failed firms. The groups should be mutually exclusive and collectively exhaustive categories (two or multi-point nominal dependent variable), and each individual belongs to one of them. These techniques can also be used to identify which significant variables contribute to making the classification.

MDA can be employed as both a descriptive and predictive technique. Descriptive uses include the investigation of mean group differences and the overlaps among groups; while predictive uses centre around the formation of classification schemes to assign objects (failed and non-failed in this study) to appropriate groups on the basis of their discriminant score. The efficiency of the discriminant function in discriminating between failed firms and non-failed firms is tested by calculating the discriminant score, referred to as Z-Score, and examining the extent of any overlap in the distribution of Z scores.

If the distribution of overlap is small, the discriminant function separates the groups (failed and non-failed) clearly. If the overlap is large, there is a low degree of accuracy in classifying failed and non-failed groups. Killough, Koh, and Tsui [1989] show that the prediction accuracy rates of bankruptcy models constructed with different statistical classification techniques do not differ significantly. In particular, logit, probit and non-parametric analysis - the primary alternatives for developing classificatory models show no one technique is consistently superior. Given that the primary research objective in this study is comparing the classificatory accuracy of models using industry relative ratios and unadjusted ratios, **the choice between MDA, logit, probit, and non-parametric** (see Chapter 2, statistical methodology review) **is not critical to this research objective.**

MDA is well suited for descriptive or inferential research questions that are not concerned with causality. Logit and probit are better suited when significance tests of individual variables are required. A non-parametric approach does not require the variables to be multivariate normally distributed. The ideal conditions for the use of MDA are more restrictive than those for logit, probit and non-parametric analysis. The ease of use of the SAS package, to particularly to perform Lachenbruch U-method [Lachenbruch and Mickey, 1968] calculations with MDA, (but not with logit, probit and non-parametric), was the critical factor in our choice of MDA technique.

5.3.2 The Objectives of MDA

MDA has been generally used for the identification of group membership based on a observation of financial attributes. The objective of discriminant analysis in this study is to classify failed and non-failed firms in some fashion so that the groups are forced to be as statistically distinct as possible. MDA develops a composite score for observations (usually by applying the Fishers'[1936] procedure of maximizing the ratio of between-groups variance to the within-groups variance). Its major purpose are establishing classification rules and statistical inference of the results (e.g. significance of the difference in group mean vectors). However, Green, et al [1978] suggested that four main objectives of two-group discriminant analysis are:

1. Testing whether significant differences exist between the average score profiles of two previously defined groups, assuming group dispersions are equal and the distributions are multivariate normal.

2. Determining which variables account most for such inter-group differences in average profiles.

3. Finding a linear combination of the predictor variables that enables the analyst to separate the groups by maximizing among group relative to within group dispersion.

4. Establishing procedures for assigning new individuals whose profiles, but not group identity, are assumed to be from one of the prior defined groups.

5.3.3 The Nature and Assumption of Linear MDA

Theoretically, there are several major assumptions central to discriminant analysis. Violation of the assumptions might cause difficulty in the interpretation of results:

1. The independent variables of each group are multivariate normally distributed;

2. The group dispersion (variance - covariance) matrices are equal across groups;

3. The populations are mutually exclusive and collectively exhaustive.

4. The vectors of means, the covariance matrix and the prior probabilities of each group are known.

If the distribution of x is not multivariate normal or one or more of these conditions do not hold, the linear discriminant function will not be an optimum assignment rule [Lachenbruch, 1975, p. 40]. In practice, the technique is very robust and these assumptions need not be strongly adhered to [Nie, et al., 1975, p. 435]. The first, fifth and sixth assumptions have been met in this study because a failed company cannot at the same time classify into both failed or non-failed groups and vice versa.

5.3.3.1 The Non-Multivariate Normal Distribution

The assumption of MDA that independent variables have a multivariate normal distribution is frequently violated. The violation of this normality assumption may bias the tests of significance and the estimated error rates using both the linear and quadratic discriminant functions [Eisenbeis, 1977, p. 875]. He [1977, p. 87] also points out that transformations may change the inter-relationship between variables and even the relative position of observations in the group. Some authors, for example Lachenbruch et al. [1973], reported that linear classification rules were sensitive to non-normal data, whereas quadratic rules were most severely affected especially when the sample size was not large. However, other authors, notably Gilbert [1968] and Krzanowski [1977], have shown that discriminant analysis is a rather robust technique which can tolerate some variation. As we have discussed many researchers focus on normality in their analysis of the distribution of financial ratios.

In this study the data, if non-normality occurs, the ratio is first transformed, and then winsorized for reducing the departure if the normality is not approximately achieved. Square root, logarithmic, and inverse transformations are applied to the ratios in order to transform them as appropriate.

5.3.3.2 The Equality of Group Variance-Covariance Matrix

In many cases, the assumption of linear discriminant analysis is that the equal group dispersion (variance-covariance) matrices are equal across all groups. Analysts generally use a test, Box's M, to obtain a statistical measure of the equality. Eisenbeis [1977] and Joy and Tollefson [1975] suggested that if the assumption of dispersion (covariance matrix) of two groups is not met, it will affect the significance test for the equality of group means; but the multivariate normality is an appropriate description of the ratio joint distribution. If the assumptions of group variance-covariance are not met, a quadratic discriminant rule rather than linear discriminant rule is required to minimize the probability of mis-classification.

Hamer [1983] examined four different variable sets used by four researchers [Altman, 1968; Deakin, 1972; Blum, 1974; Ohlson, 1980] on a data set that included 44 failed firms and 44 non-failed firms. She found that for each of the variable sets, the group covariance matrices were statistically different and the linear model performed at least as well as the quadratic version in classification success. Taffler [1981] and Altman [1981] found that linear DA tended to classify better than quadratic DA when group variances were not too much different. Quadratic DA , however, while quite accurate on original samples, is uniformly disappointing vis-à-vis linear DA in hold-out sample tests [Altman et al. 1977, and Martin 1977]. Nevertheless, Deakin [1976] found that linear DA produced better classification results for the non-failed firms, quadratic DA model's classification results were better for failed firms.

Lachenbruch [1975, pp. 46-47] suggested that if the covariance matrices are not equal, then the optimal rule is a quadratic discriminant function. For large values of Mahalanobis distance (Parameter Unknown) the quadratic and linear functions behave similarly. Marks and Dunn [1974] and Wahl and Kronwal [1977] suggest that the quadratic discriminant function performs worse for small sample sizes compared to a linear function. With multivariate normality and large sample sizes, the quadratic function performs better than the linear function when differences between dispersion (covariance matrices) are quite large. The linear DA function is better than quadratic DA when the group variances were more similar, when group means were far apart, when sample sizes were small and when the number of variables was small. Gilbert [1969] concluded that the linear and quadratic rules can result in considerably different classification results depending on the number of variables, the number of observations, and the group centroids.

In theory, the quadratic classification rule should represents the linear rule under conditions of unequal dispersion matrices. In practice, it is sensitive to non-normal data [Dillon, 1979]. However, in this study, we employed linear function rather than quadratic function because of a number of following reasons:

1. The quadratic rule is particularly sensitive to non-normal data, and hence the employing results of a quadratic DA with non-normal data may be poorer than linear DA, due to financial ratios never becoming normal;

2. The quadratic DA requires a larger sample to estimate in order to prevent over-fitting;

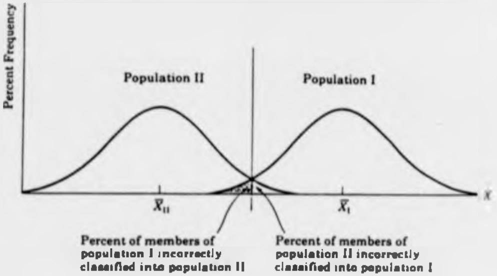
3. A quadratic rule would be more difficult to apply and interpret, using it would be less useful in practical applications.

In the case of dichotomous variables most evidence suggests that the linear discriminant rule often performs reasonably well [Gilbert, 1969]. Lachenbruch [1975, p. 45] concludes that a linear function performs fairly well for small sample sizes. It was decided to use it in this study for industry relative ratios, business cycles, and industry-specific analysis.

5.3.4 Basic Concepts of Classification

Suppose that an individual observation may belongs to one of two populations (either failed or non-failed firms). We begin by considering how an individual can be classified into one of these populations on the basis of a measurement of one characteristic, say X. The way X represents the sample from each population, how do we estimate the distribution of X and the two population mean to classify correctly into one of populations. Typically, these distributions can be represented as in Figure 5.1.

From the Figure 5-1 that a low value of X would direct us to classify an individual into population II and a high value would lead us to classify an individual into population I. A low and high value was defined by a dividing point, say C. If the X >= C then we will classify an individual into population I (non-failed firms). If the individual came from population I but the measured X were less than C, dividing point, we will incorrectly classify the individual into population II, and vice versa.



Hypothetical Frequency Distributions of Two Populations Showing Percentage of Cases Incorrectly Classified (Source: Afifi and Clark, 1984, P. 250)

If the two populations have the same variance, then the **dividing point of C** is

$$C = \frac{\bar{X}_I + \bar{X}_{II}}{2} \tag{5.1}$$

Where:

$\bar{X}_1$ = the average value of X in population I

$\bar{X}_2$ = the average value of X in population II

For this value the two probabilities of error are equal. In other words, the degree of overlap of the two distributions is frequently large and the variances are precisely equal. Now consider 2 variables X_1, and X_2. The dividing line between two populations was presented by Fisher [1936] as an equation Z = C, where Z is a linear combination of X_1 and X_2 and C is therefore a constant. The dividing point, can then be expressed as follows:

$$C = \frac{\bar{Z}_I + \bar{Z}_{II}}{2} \tag{5-2}$$

Where:

$\bar{Z}_I$ = the average value of Z in population I

$\bar{Z}_{II}$ = the average value of Z for population II

For the two variable case, the Fisher discriminant function Z is as follows:

$$Z = b_1X_1 + b_2X_2$$

Where:

b_n = the discriminant coefficients

5.3.5 Linear Discriminant Function

Fisher [1936], in his linear discriminant function did not make any distributional assumptions for the variables used in classification. Thus, he attempted to classify group membership by forming one or more linear combinations of discriminating variables. These discriminant functions are expressed as follow :

$$Z_i = b_0 + b_1X_{1i} + b_2X_{2i} + ... + b_nX_{ni} \quad (5\text{-}3)$$

Where:

Z_i = the i^{th} company discriminant score,

b_n = the discriminant coefficients , n = 0, 1,2,3...b_n variables;

X_{ij} = the ith company's value of the jth independent variable.

In general, selecting the optimal discriminant functions, the Fisherian approach advocates the maximization of the ratio of the among - groups sum of squares on the function to the pooled within - groups sum of squares on the function (see: Cooley and Lohnes, 1971, p.246). To select the optimal discriminant function(s), the following ratio is maximized:

$$\text{Maximize } L = \frac{\text{Between Group Variance}}{\text{Within Group Variance}}$$

$$= \frac{[\, \bar{Z}_I \;-\; \bar{Z}_{II} \,]^2}{\sum_{i=1}^{2} \sum_{j=1}^{n_i} [\, Z_{ij} \;-\; \bar{Z}_i \,]^2} \qquad (5\text{-}4)$$

where:

$\bar{Z}_i$ = the mean discriminant score for group i, i = I , II.
n_i = the number of individuals in group i.
Z_{ij} = the score of the jth individual of group i.

Once the discriminant functions have been derived, the resulting assignment rule is to classify an individual according to its discriminant score (Z_i) as follows: Let Z_c be the dividing point for the discriminant score. Then the classification procedure is:

If $Z_i > Z_c$, classify individual i as belonging to group I;
If $Z_i < Z_c$, classify individual i as belonging to group II.

Every individual on one side of Z_c is classified as group I; on the other side, as group II (in this study these are failed and non-failed firms). The classification procedure permits an interpretation of the impact of each of the independent variables. From illustration, suppose the independent variable X_1 = NI/TS and the higher the value of Z_i, the more likely that the company is solvent. If the sign of b_i is positive then higher values of X_1 implies a better solvency. The larger the size of b_i the more important variable X_1 is in discriminating between Group I and Group II.

5.4 Evaluating the Significance of Independent Variables

5.4.1 Introduction

The selection of the relevant ratios to be included in an MDA model is problematic given the lack of an underpinning theory. It is common practice to select a large number of ratios and then to factor analyse or regress them in order to select the most representative set of ratios to reflect the information contained in the sample. Because data over time and across industries may not be consistently stable or available, there is no guarantee that the same set of ratios would be selected for the same set of companies for a various of years prior to failure. Also, different researchers have ended up with alternative variable sets after analysing similar data. It is, however, often assumed that the results of a particular analysis can be used for time periods different from the one for which the data was collected; the implicit assumption being one of stability in the structure of financial ratios. However, evidence on the non-stability in financial structures in the UK has been reported by Ezzamel, Brodie and Mar Molinero [1987]. Zavgren [1983] is to evaluate the predictive value of variables not included in her study. For example, data from the statement of changes in financial position has been available only since the early 1970s. Ratios developed from this data should be investigated for their information content regarding bankruptcy. Macro-economic variables could also be important in making a distinction between failing and non-failing firms. To a large extent the effects of these variables are reflected in financial statement data but with a significant lag. Rising interest rates, a recessionary environment, the availability of credit and other macro-economic factors could all affect the firm's vulnerability to failure. Further research to determine the effects of such variables is reported in chapter 9.

5.4.2 Selection of Variables in the Discriminant Model

Variable selection methods are used mainly in exploratory situations where many independent variables have been measured and but they choice for explaining the situation has not been finalised. The goal to discover the 'optimal' subset out of the raw data the least number with the greatest discriminating ability. The researcher may have some prior theoretical justification for using certain variables but may remain open to suggestion for the remaining variables.

5.4.3 The Function's Overall Significance

The statistical significance of a discriminant function shows whether the observed between-groups differences are greater than would be expected by chance. This determines if there is any hope of classifying future observations using the given variables (Lachenbruch, 1975).

The null hypothesis being tested is that none of the variables improve the classification based on chance alone. Equivalent null hypotheses are that the two population means for each variable are identical, or that the population D^2 (Mahalanobis distance) is zero, or the variable means for two population are identical. The test statistic for the null hypothesis is

$$F = \frac{N_1 + N_2 - K - 1}{K \ (N_1 + N_2 - 2)} \times \frac{N_1 \times N_2}{N_1 + N_2} \times D^2 \quad (5\text{-}5)$$

Where:

N_i = the number of observations from group i.

K = the number of independent variables.

The resulting F-statistic has K and $N_1 + N_2 - K - 1$ degrees of freedom D^2 is the Mahalanobis's distance which is the difference between the group means of the discriminant function:

$$D^2 = \sum_{i=1}^{K} b_i \quad (\bar{X}_{i1} - \bar{X}_{i2}) = (\bar{Z}_1 - \bar{Z}_2) \qquad (5\text{-}6)$$

Where:

bi = the discriminant coefficient of the ith variable.

$\bar{X}$ij = the mean of the ith variable of the jth group.

$\bar{Z}$j = the mean discriminant score of the jth group.

However, the statistical significance is a first necessary step but it is not a good indicator of the efficiency of a discriminant function (Morison, 1969), so the latter can be evaluated by classifying other samples.

5.4.4 The Relative Importance of Independent Variables

The relative importance of each independent variables can be measured by one of the following methods:

(1) Standardised Discriminant Coefficients

The standardised discriminant coefficients rank variables according to their contribution. The relative effect of each variable on the discriminant function can be obtained from the standardized discriminant coefficients. This technique involves the use of the pooled (or within-group) covariance matrix from the computer output. The larger the standardized discriminant coefficient value, the greater its contribution. The standardized discriminant coefficients are illustrated in the following example: assume in the analysis sample the coefficient of b_1 = 0.023 and b_2 = 0.034, the covariance matrix is as follows:

	R1	R2
R1	300.2	-46.5
R2	-46.5	200.2

The pooled standard deviations are $\sqrt{300.2}$ = 17.32 for R1 and $\sqrt{200.2}$ = 14.14 for R2. The standardized discriminant coefficients are (0.023) x (17.32)=0.398 for R1 and (0.034) x (14.14) = 0.48 for R2. It is therefore seen that R2 has a relatively larger contribution to the discriminant function than R1. Although the important variable determines the discriminant score, Lanchenbruch [1975, p. 29] suggests that this method is not commonly useful and has its limitations, because the coefficients are determined only up to a constant multiple.

Joy and Tollefson [1975] also suggest that standardized coefficient may be incorrect. They recommended a "separation-of-means" measure which was suggested by Mosteller and Wallace [1963] and is based on the proportion of Mahalanobis Distance. The term D^2 can be interpreted as the squared distance between the means of the standardized value of the discriminant function. A larger value of D^2 indicates that it is easier to discriminate between the two groups. In general, the greater D^2 for the two populations, the lower is the probability of mis-classification.

(2) Mosteller and Wallace Method

Mosteller and Wallace [1963] assesses the importance of a particular variable in terms of the proportion of Mahalanobis's distance, D^2, which is defined as:

$$r_k = \frac{b_i \ (\bar{X}_{i1} - \bar{X}_{i2})}{\sum_{i=1}^{k} b_i \ (\bar{X}_{i1} - \bar{X}_{i2})} \qquad (5\text{-}7)$$

Where:

r_k = the relative importance of the kth variable;

b_i and $\bar{X}_{ij}$ are defined above in equation (5-6).

The relative contribution of a variable r_k should have the same sign of the other variable's contributions. This sign must be positive if we assume that group 1 is the non-failed group. Thus, the relative contribution of each variable must be positive and all the contributions must sum up to unity. If any of the latter two conditions does not hold, the model is not consistent and is unacceptable (see: El Hennaway and Morris, 1983, Taffler, 1982). Taffler [1982] argues that

"a variable's negative contribution may be due to multicollinearity, sample bias or very unequal dispersion matrices, then it is not possible to interpret the associated variables in any meaningful way and suggests the removal of such a variable"

(3) Conditional Deletion Method

This method removes each variable in turn from the k-variable set, with replacement, and the variables are ordered according to the resulting reduction in overall discriminating power as measured by the (k-1) variables' F-statistic. The Wilks' lambda computed which corresponds to the k-1 remaining variables is called the residual Wilks' lambda of the variable that has been removed. The variable with the highest residual Wilks' lambda is the most significant in the k variable discriminant function. This method was used in previous studies (e.g. Sudarsanam and Taffler, 1985, Taffler, 1982). The conditional deletion method has the most appeal since it considers the correlations among the variables and measures the importance of a given variable to the multivariate F-statistic conditioned upon the others in the variable set which have already been incorporated [Altman and Eisenbeis, 1978].

However, it appears that there none of the above methods is generally accepted as a measure of the relative contribution of each independent variable. Although, Mosteller and Wallence [M & W] method appears to be measuring that contribution it cannot reveal how the contribution of the interaction between the variables affects that of each variables. Eisenbeis [1977, p. 884] criticises the use of the [M & W] method in that the weights are difficult to interpret because they are signed; can be greater than one; do not sum to one; and that the method is not generalizable to more than two groups. Altman and Eisenbeis [1978, p. 190] suggest that if the variables are uncorrelated, there will be strong agreement among the rankings discussed above.

5.5 Incorporating Prior Probabilities and Misclassification Costs

A prior probabilities refer to the probability of an observation actually arising from each of the groups in the population. Assignment procedures usually incorporate a prior probabilities to account for the relative occurrence of observations and costs to adjust for the fact that some classification errors are more serious (costly) than others. Prior probabilities are important because they directly influence the classification results. Unequal prior probabilities cause more observations to be assigned to those groups with larger prior probabilities and assign fewer observations to those with smaller probabilities. The importance of the a priori probabilities and costs of misclassification have not been widely discussed in the literature. In many papers authors, ignore error costs and assume that group membership was equally likely.

Ideally, the prior probabilities should reveal the probability of failure for the different time period and sample for which predictions are to be made. However, in the absence of theoretical guidance, estimating the prior probability of company failure is more difficult because (1) observations from a single period in time are used to form classification rules and make predictions about group membership in a future time period or periods, (2) the relative expected occurrences of the groups in the population may vary from period to period [See Eisenbeis, 1977, p. 890].

Assuming equal probabilities of failed and non-failed firms, the linear discriminant method will establish a cutoff point at the mid-point between the two group mean discriminant scores. This is pertinent if there is an equal probability of group membership; and it seems consistent with studies that were based on samples with equal observations in the failed and non-failed group. However, Eisenbeis [1977] and Palepu [1986] suggest that the use of different cutoff probabilities will influence the classification results of the model. It is necessary to identify the decision context of interest and estimate the a priori state probabilities of a firm in order to determine the optimal cutoff probability between the groups. If the correct priors are not considered, the classification results can be misleading. Therefore, estimating the prior probabilities of failure prediction had better heed the following previous studies' suggestions:

1. Meyer and Pifer [1970] have used a trial and error method and found that a 50-50 rule minimized their classification errors in the sample rather than providing evidence on the population error rates. Alternative sampling methods such as the "pairwise sampling" methods, have been used by many authors as representative of non-random schemes. Non-random methods where certain confounding factors are controlled (such as firm's size, number of branches, and location, and industry difference...etc) are appropriate for investigating the importance of certain variables but not for estimating classification error rates.

2. Jones [1987] states that in bankruptcy prediction studies, one can expect that the prior probabilities of membership will be much lower for bankrupt firms than nonbankrupt firms. In light of the unequal prior probabilities, the optimal cutoff is given by adjusting the cutoff score by an amount, X, which is given by $X = \ln [P_1 / P_2]$, where P_1 and P_2 represent the prior probabilities of two groups. Assuming P_1 represent the probabilities of failed firms and P_2 represents the probabilities of non-failed firms, $P_1 + P_2 = 1$, P_1 is less than P_2. The adjustment will move the cutoff score away from the mid-point between group means and closer to the failed firms (Group I) mean. This makes the classification discriminant score of an observation closer to the mean of group one. On the contrary, classification into Group II becomes more likely. This tendency to favour Group II results in misclassifying more Group I members into the Group II, but misclassifying less Group II members into the Group I. Because there are so many more Group II members, the overall classification

success is improved by the adjustment. Jones [1987] states that failure to consider prior probabilities is a valid criticism of earlier studies that assumed equal probability of group membership or probabilities based on sample proportions.

3. The population's prior probabilities and costs of misclassification should be considered if the model is to be used for decision-making purposes. This was subsequently done by Taffler [1977a and 1977] in two studies, for which he obtained a group of financial analysts' estimates of the prior probability odds of failing to non-failing for UK companies. These were 1:10 in the first study, and 1:7 in the second. The cost of misclassifying a failed firm as non-failed and the cost of misclassifying a non-failed firm as failed firm is (C1/C2) 40:1.

According to the argument made by Joy and Tollefson [1975] the population's prior probabilities should be included for:

1. Evaluating the expected performance (EP) if the linear discriminant function is to be used in classifying other samples which are drawn at random from the population. This evaluation is made by comparing the expected performance of a discriminant function on a random sample (EP_{DF}) with that of the proportional chance criterion (EP_{prop}) which are defined as :

$$EP_{DF} = q_1 \, (n_{11} \, / \, n_{1.}) + q_2 \, (n_{22} \, / \, n_{2.}) \qquad (5\text{-}8)$$

Where: q_1 and q_2 are the population's prior probabilities of failure and non-failure. n_{ii} is the correct classification of group i and $n_{i.}$ is the total companies in group i (see: Table 5-9).

$$EP_{prop} = (q_1)^2 + (q_2)^2 \qquad (5\text{-}9)$$

It should be noted that the population's prior rather than the sample frequencies are used above. Also, the proportional rather than the maximum chance criterion is used above. Morrison [1969] argued that, since the discriminant function defies the odds by classifying an individual in the smaller group, the chance criterion should take this into account and therefore the proportional choice criterion should be used.

2. Evaluating the expected cost (EC) : The misclassification costs are used to evaluate the expected cost of using a discriminant function in making decisions. The two costs are calculated as follows:

$$EC_{DF} = q_1 \, (n_{12} \, / \, n_{1.}) \, C_1 + q_2 \, (n_{21} \, / \, n_{2.}) \, C_2 \qquad (5\text{-}10)$$

$$EC_{prop} = q_1 \, q_2 \, C_1 + q_1 \, q_2 \, C_2 = q_1 \, q_2 \, (C_1 + C_2) \qquad (5\text{-}11)$$

Where :

n_{ij}
= the number of firms of Group i misclassified in group j,

$(n_{12} / n_{1.})$ and $(n_{21} / n_{2.})$
= the proportion of type I and type II errors, respectively.

$q_1 (n_{12} / n_{1.})$ and $q_2 (n_{21} / n_{2.})$
= the probabilities that a randomly selected entity will be misclassified by the discriminant function, and

C_1 and C_2
= the costs of misclassifying a failed and non-failed firms, respectively.

The discriminant function would be superior to the proportional chance criterion if and only if $EC_{DF} < EC_{prop}$. Under the condition of the above evaluation, the population's prior probabilities and the ratio of C_1 / C_2 must be known. The latter needs not to be known exactly. It is sufficient to know that the ratio C_1 / C_2 is greater or less than some critical number (see: Joy and Tollefson, 1975). To estimate the prior probabilities of this study, the period from 1974 through 1985 is chosen. Statistics on bankruptcy rates are hard to come by Dun and Bradstreet (see p 91) estimate the rate at under 2%. The average rate of removal of public firms under review 1974-1985 was 11.25% (6.63% + 6.61% +...+16.5%) / 12 = 11.25%. This figure represents all types of reasons for removal including liquidations (including 'members voluntary' liquidation) and also **small, medium, and large** companies in Great Britain (i.e. **England, Wales and Scotland**). Since the mortality rate seems to vary with the firm size, location, and industry across the years 1974 to 1985, it can be reasonably argued that the ratio for large size companies (the subject of this study) would be about one-quarter of the observed rate [see Ukaegbu, 1987, p. 208]. Assuming 3% represents the mortality rate for large companies in this study. However, estimating the prior probability of corporate failure is not easy task because of the above described reasons. Therfore, the prior probability for the present study is therefore 0.97 : 0.03 to reflect the decision context. (i.e. 3% failure likelihood). The subjective estimates realistic prior probability of failure at 3% is used in this study. However, in order to compare the results with the sample prior probabilities and previous studies (see: Table 7-10). In this study, we employed sample prior probabilities and then realistic prior probabilities.

Table 5-8 Summary of Changes in the Number of Public Companies on the Registers: 1974 / 1985

Year	Registers at 31 Dec	Of which,in liquidation or course of removal	Effective number on registers at 31 Dec.	Mortality Rate
1974	16658	1105	15553	6.63%
1975	16695	1105	15590	6.61%
1976	16716	1131	15585	6.76%
1977	16819	1184	15635	7.03%
1978	16954	1129	15825	6.65%
1979	17154	1139	16015	6.63%
1980	10325	1162	9163	11.25%
1981	9206	1188	8018	12.90%
1982	6511	1187	5324	18.23%
1983	6508	1173	5335	18.02%
1984	6589	1182	5407	17.93%
1985	7186	1186	6000	16.50%
Total	147321	13871	133450	11.25%

Source: Department of Trade Companies (1974-85) Annual Reports

Two types of errors may arise in classification: type I and type II errors. The type I error is analogous to that of an accepted loan to a company that later goes bust. The type I cost is then the loss in making a loan to a company that later goes bankrupt. This implies that the bank will loss interest on the loan and a good part of the principal. On the other hand, a type II error is analogous to that of a rejected loan that would have resulted in a successful payoff. The type II cost implies the loss in not making a good loan. In this case, the bank may decide instead to invest the money in a safe government security, like the Treasury Bills even though the return may not be as high if the bank had granted the loan. The bank therefore loses the interest differential between the two investments. But this loss (of making the type II error) is much less than the first (of making the type I error). The difficulty in integrating the cost concept in a classification model lies in trying to determine actual values for these costs.

Optimal cutoff points and accuracy rates for the model were determined by different relative levels of misclassification costs. Unfortunately, in the context of different types of business using failure prediction models to assess the non-failed status of firms, misclassification costs are largely unknown. Analysts who consider costs typically provide results for a wide range of costs specifications. This was done in the research of Altman, Haldeman, and Narayanan [1977], Frydman, Altman, and Kao [1985]. In practice, the cost of misclassifying failed firms as non-failed is likely to exceed the cost of misclassifying non-failed firms as failed. The expected misclassification costs of using the model were computed for five different cutoff points, corresponding to the ratio of CI to CII ranging from 1:1 to 40:1. This range was selected because the misclassification cost of a Type I error is expected to be higher than that of a Type II error (i.e. CI > CII), hence, the ratio 1:1 is a lower limit. Further, Taffler [1982] estimate that Type I error cost as being some 40 times greater than the Type II error. Hence, 40:1 is an upper limit in this study. These choices are admittedly arbitrary since misclassification costs are likely to be user- and situation-specific. The results are therefore merely suggestive of the relative performance of the respective models and their sensitivity to a change in the classification criterion.

5.6 Classification Test

The classification of companies other than those of the initial sample is the most important and acceptable test of a discriminant function's classifying and predicting powers. The classifying power involves specification of the function which best separates the groups. The predicting power consists of developing a classification matrix to further evaluate the discriminant function. These tests of a function's classifying and predicting powers require determining a cut-off score, computing the discriminant scores of the companies of the cross validation samples and compute the efficiency measures.

5.6.1 Testing the Discriminating power

The initial (ex post) sample is that which is used to develop a discriminant model or to fit a discriminant function. The cross validation sample is similar to the initial sample but is saved to test the classifying power of a discriminant function. In terms of the split sample technique the sample of companies covering a particular period of time is divided into two subsamples; one of which is the initial sample and the other is the cross validation sample which is also referred to as the calibrating or hold-out sample. Using the split-sample technique can lead to poor estimates and erroneous conclusions about the error rates that apply to the linear discriminant function based on the entire sample when data is often scarce and small samples are common. The method requires large sample sizes in order to obtain both a good estimate of the discriminant function and to simultaneously evaluate its performance. Neter [1966, p. 112] stated, in his comments on Beaver's 1966 study that:

it is desirable to use calibrating samples where, in effect, half of the data, is used in order to develop the criterion and the other half is used to test the predictive power of the criterion (p.112).

In this study, the split sample technique (forecast) is employed in chapter 7 because of large sample sizes.

In order to eliminate the upward classification bias the discriminant function should be used to classify the firms in the hold out (ex ante) sample. Thus, the discriminant coefficients are used to compute the discriminant score of each company in the hold out sample, then the cut-off point is used to classify the companies into one of the two groups and the results are presented in a classification matrix of the form of Table 5-9 below. The efficient classification of the cross validation sample proves the ex post discriminating power of the computed function, but it does not provide evidence on the function's ex ante predictive power. Lachenbruch proposed the leave-one-out (or U) method (see: Lachenbruch and Mickey, 1968 for the method's performance). This method holds-out one observation at a time, estimates the discriminant function based upon $n_1 + n_2 - 1$ observations and then classifies the held-out observation. This process is repeated until all observations are classified. The disadvantage of this method is that it requires the computation of $n_1 + n_2$ discriminant functions for each function to be tested. Application of the model to sample data and analyzing the overall accuracy in terms of the percentage of observations correctly classified as well as the analysis of Type I and Type II errors are the general validation procedure. Leaving-one-out method is particularly useful to researchers who must deal with small sample size.

Hamer [1983], whose sample included only 44 failed firms, and Dambolena and Khoury [1980], whose sample had only 23 firms, used the Lanchenbruch technique. Eisenbeis [1977] states that the Lachenbruch U-method gives almost unbiased estimates of the confidence intervals. Intuitively, one would expect the method to be more efficient than the hold-out method. Kshirsager [1972] feels the method may not be sensitive to the normality assumption. Eisenbeis and Avery [1972] have applied it to problems with unequal dispersion and more than two groups. Since the sample size in chapter 8 (three business cycles) and chapter 9 (industry-specific models) is small, implying that the Lachenbruch validation technique will be used to test the classifying power of failure prediction models.

5.6.2 Testing the Predictive Power

Given that classifying power tests do not provide evidence on a model's predictive ability, Joy and Tollefson [1975] suggest that this power can be tested by classifying the firms of the validation sample. The efficient classification of the validation sample provides successful evidence on the predictive power of a discriminant function. The results of the classifying and predicting tests are presented in the following classification matrices of the following form.

Table 5-9 Classification Matrix

Actual Group	Classified As		
	Failed	Non-Failed	Total
Failed	n_{11}	n_{12}	$n_{1.}$
Non-Failed	n_{21}	n_{22}	$n_{2.}$
Total	$n_{.1}$	$n_{.2}$	n

Where:

The first subscript in n_{ij} refers to actual group while the second refers to the classification group.

The purpose of these matrices is to prepare for computing the measures of the discriminant function's classification accuracy (see: Joy and Tollefson, 1975). The unequal sample sizes introduce a potential problem in statistical evaluation. The problem exists because the group of interest is usually the smaller group, and the accuracy in classifying that group is obscured by the accuracy in classifying the larger group. Total classificatory accuracy and one marginal accuracy measure are employed. Total classificatory accuracy asks how well the model did in classifying both failed and non-failed firms, and is computed by $(n_{11} + n_{22}) / n$ in Table 5-9. The marginal classification, computed as $(n_{11} / n_{1.})$ and $(n_{22} / n_{2.})$ measure the probability of correctly classifying a failed and non-failed firms. However, these measures should be compared with the results of other classification strategies.

5.7 Statistical Significance of Models

There are two issues to answer about the effectiveness of statistical models. The first issue is whether the models perform better than a chance model. The second issue, the main focus of the study, is whether one model is superior to another in failure predictive ability. Thus, two categories of statistical tests are conducted in both the ex post and ex ante samples. The first category are tests of significance of individual models. These tests determine whether predictive ability from the individual models perform better than predictive ability from a chance model.

As Morrison [1969] and Sudarsanam and Taffler [1985] note, in most situations the appropriate chance model to use is the proportional chance model. This benchmark model is given as:

$$Z = \frac{Q - P}{\sqrt{P(1 - P) / n}} \qquad (5\text{-}12)$$

Where:

Q = the correct classification rate of the model

P = the proportion one expects by chance, and

n = the number of firms in the sample

The second category of tests to be conducted are comparisons between models. Tests between models do not test whether models are superior to a chance model. Rather, these tests compare performance between two competing models. The focus of these tests is thus not accuracy of one model but comparative accuracy between models. The two-sided chi-square test for differences in probabilities is applied to the total classification accuracy for related samples. Elam [1975] and Mensah [1983] have employed the statistic test they referred to as Conover's T (Conover, 1971, p. 146) When the notation is defined by relating the elements as follows:

	O_{11}	O_{12}	$n_1 = O_{11} + O_{12}$
	O_{21}	O_{22}	$n_2 = O_{21} + O_{22}$
Totals	M_1	M_2	$N = n_1 + n_2$

The result of each predictive test is recorded in a two-by-two array with each element as described in Table 5-10.

Table 5-10 Two By Two Contingency Table

Number of Firms Correctly Classified With First Data	Number of Firms Incorrectly Classified With First Data
Number of Firms Correctly Classified With Second Data	Number of Firms Incorrectly Classified With Second Data

For each contingency table a test statistic 'T' is computed by the following formula:

$$T = N\ (O_{11} \times O_{22} - O_{12} \times O_{21})^2 \ / \ n_1 n_2 \times M_1 M_2 \qquad (5\text{-}10)$$

Where:

N = the sum of the sample to which the models were applied
$= n_1 + n_2 = M_1 + M_2$

O_{11} = the total number of firms correctly classified by Model 1

O_{12} = the total number of firms incorrectly classified by Model 1

O_{21} = the total number of firms correctly classified by Model 2

O_{22} = the total number of firms incorrectly classified by Model 2

n_1 = the number of firms in the sample to which Model 1 was applied
$= O_{11} + O_{12}$

n_2 = the number of firms in the sample to which Model 2 was applied
$= O_{21} + O_{22}$

$M_1 = O_{11} + O_{21}$

$M_2 = O_{12} + O_{22}$

The null hypothesis is rejected

for $\alpha = 0.05$ when $T > 3.841$,
for $\alpha = 0.10$ when $T > 2.706$,
for $\alpha = 0.20$ when $T > 1.642$, and
for $\alpha = 0.25$ when $T > 1.323$.

The strongest case for rejection of the null hypothesis occurs when $T > 3.841$.

5.8 Summary and Conclusions

The main methodology and hypotheses discussed in this chapter are a discussion of research design, sample selection, data analysis and multivariate discriminant analysis. Failed and non-failed firms are derived from Datastream using a matching approach on the basis of similar industry size and corresponding year so as to avoid major industry differences and specific-time sampling biases. Large sized firms rather than small firms are drawn in this failure prediction study. Forty-one significant financial ratios and macro-economic variables popular in the previous literature are used in here ignoring accounting policies of firms, because the adjusted and considered accounting ratios did not provide better predictive ability or information over and above traditional (accrual-based) accounting ratios [see Casey and Bartczak, 1984 and Skogsvik, 1990]. A number of studies [Keasey and Watson, 1987b, 1988; Peel and Peel, 1987] have examined the predictive content of the lag in submitting accounts and non-financial or qualitative variables, and found them to have insignificant information content in their study. Therefore, these variables have not been included in this study because they did not obviously provide better information.

One popular statistical method, discriminant analysis, is used in this study as a data analysis tool. Discriminant analysis classifies a company into one of two groups on the basis of a statistic (Z-score) that is a weighted combination of ratios that best discriminate between the two groups of firms. The method assumes that the ratios are from a multivariate normal distribution and the covariance-matrices are equal. In theory, linear discriminant analysis (LDA) is more appropriate when the covariance matrices are equal for two groups. Quadratic discriminant analysis (QDA) is more appropriate when the variance-covariance are unequal for two groups. In practice, however, the predictive ability of QDA for unequal variance-covariance drops when the number of independent variables is large relative to the sample and the sample size is small. The review of this chapter suggests that we did factor analysis but did not use it because the financial ratios in each factor loading vary over time and across industries. It is difficult to interpret on the basis of the results. Therefore, we decided not to rely on the results of factor analysis in the present study. The next chapter introduces the empirical results of data analysis based on univariate analysis. We also present the results of examining the ratios for the outliers, data distribution and alternative transformation method and correlation analysis.

Chapter 6 Preliminary Empirical Results

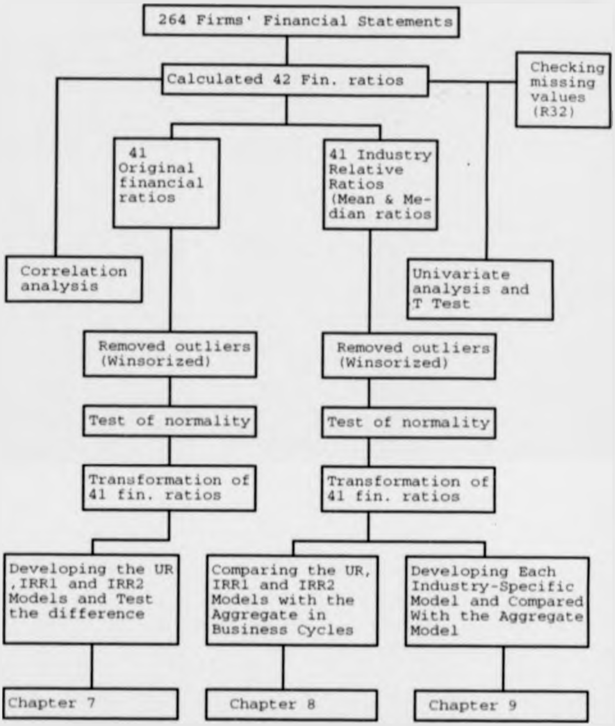
6.1 Introduction

Chapter 6 presents the preliminary empirical results of the study. The initial choice of independent variables included 41 financial ratios, year dummy variables, and economy-wide indicators. We discuss the definition of the financial ratios, the treatment of missing values, tests of normality and the descriptive statistics for each ratio. We also examine the transformations and examines the correlations between each ratio. The univariate comparisons between the mean values of each ratio for the failed and non-failed firms are reported in this chapter. The objective of these preliminary comparisons is to inform the selection of ratios which will most effectively differentiate between failing and non-failing firms.

6.2 Financial Ratios and Missing Values

There were very few missing values for each case. A popular method to cope with missing values is to replace initial value with 9,999 rather than the expected maximum value of the ratio. Some substitution is important since if a firm is missing just one observation, then the firm will be excluded from the whole analysis. Any inclusion of cases with incomplete or missing values will influence the classification accuracy and bias the estimates. Initially, 42 financial ratios were considered in this study. (See Appendix A). R32, the interval credit ratio, defined as ((current assets - stocks - current liabilities) / (sales - depreciation - profit before tax) / 365) was excluded because of missing account item values.

Table 6-1 A Comprehensive Flowchart of Preliminary Empirical Results



Note: Fin = Financial, MDA = Multivariate Discriminant Analysis, UR = Unadjusted Ratios, IRR1 = Industry Mean Ratios, IRR2 = Industry Median Ratios.

6.2.1 A Priori Groupings

Financial attributes can be measured through the use of financial ratios which express a relationship between two financial items (or an aggregate of items), that are contained in published financial statements. For the purposes of description financial ratios can be grouped into categories, although Pinches, Mingo and Caruthers [1973] criticized a priori groupings of ratios and proposed an empirical taxonomy to take into account the relationships between and among the ratios. There are alternative schemes presented in the literature. Bernstein [1983, p. 81] states ratios can be grouped in six categories: (1) short-term liquidity, (2) funds flow, (3) capital structure and long-term solvency, (4) return on investment, (5) operating performance, and (6) assets utilization.

There are many useful ratios reported in the literature. The problem in developing a discrimination model is to identify a limited set of financial ratios. Naturally, different researchers often include different ratios. Accounting ratios have been grouped by previous authors according to the firm's financial attributes, on an a priori basis, into different numbers of categories - e.g., profitability and liquidity (see: Foster, 1978, p.28). In this study, however, each ratio used in measuring financial attributes is categorized into one of eight factors on the basis of **a priori similarity** among themselves and their inter-relationships according to Chen and Shimerda [1981], Pinches, Eubank, Mingo, and Caruthers (1975), and Barniv and Raveh's [1989] studies. They are: (1) Profitability, (2) Capital turnover, (3). Financial leverage, (4). Liquidity, (5). Cash position, (6) Inventory turnover, (7) Receivable turnover, and (8) Other ratios. A priori groupings in this study is mainly based on Chen and Shimerda's Study (See Appendix A).

6.2.2 The Problem of Outliers

Cochran [1963] has pointed out that outliers cause increases in the sample variance and thus decrease the precision of parameter estimates. There are alternative strategies to deal with the presence of outliers in data sets, (1) to proceed with analyses without dealing with them, or alternatively (2) to resort to various techniques of dealing with outliers (such as trimming the data by excluding the smallest and largest observations and then proceeding as if the trimmed sample were a complete one). If the sample is drawn from a normal population, the trimming procedure results in some loss of efficiency in estimating the location parameters (e.g., mean). However, if the distribution is long-tailed, efficiency is increased by trimming [Lev and Sunder, 1979]. The technique known as winsorizing can be used to change extreme values to those of the nearest non-outlier rather than delete them, and then attempting to fit the distribution with a known one, (for which data transformations have been suggested). For normally distributed samples, winsorized means are more stable than trimmed means. It should be noted that the handling of extreme values remains to some extent a subjective matter.

In this study, Taffler's approach to the deletion of outliers has been employed. Taffler [1982] suggested an approach which transforms the data to improve normality, for example, by using square root, logarithmic or reciprocal transformations. If after being transformed the distribution still contained extreme outliers, he proposes that the data is winsorised. Extreme values, in this study, were identified and excluded by means of a semi-automatic procedure which involved the following steps:

1. Summary statistics were calculated for the full data set and the histograms of the distribution, the descriptive statistics and normal probability plot were generated.

2. Any ratio point falling outside the range: mean plus or minus four standard deviations, was replaced by the sample mean. Those observations falling between 2.5 standard deviations and 4 standard deviations from the mean, were replaced by a value 2.5 standard deviations away from the sample mean.

Empirical support for the validity of this approach is offered by Frecka and Hopwood [1983] used Deakin's original ratios for a later time period and found that by deleting outliers normality could be achieved for most ratios. It is worth noting that the mean and the standard deviation used in the process of identifying outliers was calculated for the two groups separately. The results in this and the subsequent analysis are based on the revised ratios.

6.2.3 Data Distribution and Transformation

As will be discussed later, discriminant analysis, (which has been the most popular method in predicting failure prediction), requires that independent variables are multivariate normally distributed. A necessary condition is that each independent variable has a normal distribution. Transformations may change the inter-relationships between variables and affect the relative positions of the observations in a group [Eisenbeis, 1977]. Financial ratios are unlikely to be normally distributed but be skewed [Barnes, 1982]. Bird and McHugh [1977] in Australia, used five financial ratios for over 68 Australian firms in 1967, 1969, 1971. They tested the normality of the distributions for the five ratios and found financial leverage and efficiency ratios were generally normally distributed; quick assets and working capital ratios were not normally distributed; but found no conclusive results in the case of the probabilities. Buijink & Jegers [1986] in Belgium and Bougen and Drury [1980] suggested that normality for both the whole sample and the individual industry were rejected. McLeay [1986]; in the UK, and Deakin [1976]; Frecka and Hopwood [1983]; So [1987]; and Karels & Prakash [1987] in the USA, used normal distribution ratios as the main criterion for the selection of discriminating variables to offer a better fit for their models. [see Table 6-2].

Frecka and Hopwood [1983] tested the basic hypothesis of normality in 11 financial ratios for American companies over the 1950-1979 period for a large population of manufacturing firms. Statistical tests indicated that ten of the 11 raw data ratios tended to depart from normality in a highly significant manner. They indicated that transformations alone did not significantly improve the approximation to normality in the distribution of the ratios. Outliers had to be deleted before significant improvements in the distribution could be attained. So [1987], however, reported that outliers were not the only source of non-normality. After removing outliers, it was found that many ratios remained non-normally and asymmetrically distributed. Of course, one must be careful that meaningful ratio values are not deleted. In the small sample sizes characteristic of bankruptcy studies, one must be particularly careful when discarding any observation. Given this, it was decided to test first for normality in the 88 failed firms and then in the 176 non-failed firms.

Logarithmic, square root and reciprocal functions are generally the most common transformations used and they are recommended in the literature. These three transformations cannot be used for distributions which include zero values. In addition, logarithmic, and square root transformation cannot cope with negative values. Thus, a constant is added to each original ratio in order to transform all values of a given negative ratio to non-negative value. An estimated constant has been proposed to improve normality of each ratio if it is negative. A general family of transformations studied by Box and Cox [1964] was used as the basis for selecting $\lambda_2 = \min(X_j)$ as an estimated constant. The Box and Cox transformations are defined as follows:

$$X_i^{(\lambda)} = \frac{(X_j + \lambda_2)^{\lambda_1} - 1}{\lambda_1} \qquad \lambda_1 \neq 0$$

$$= \ln (X_j + \lambda_2) \qquad \lambda_1 = 0$$

Where:

X_j = the original value of the financial ratios,

$X_j^{(\lambda)}$ = the transformed value,

λ_1 = the transformation parameter,

λ_2 is chosen so that $X_j + \lambda_2 > 0$.

For numbers of the family were chosen for investigation, $\lambda_1 = 1$; $\lambda_1 = 1/2$; $\lambda_1 = 1/3$; $\lambda_1 = 0$, i.e. no transformation, square roots, cubic roots, and natural logarithms. The shape of the distribution of the transformed data is usually different from the shape of the distribution of the original data. This is due to the non-linearity of the transformation. It is possible, as Box and Cox [1964] have shown, to employ the tools of standard statistical analysis in order to derive the exact distribution of the transformed data from the distribution of the original data. The distribution of some ratios appear to be bounded by zero and tail off towards positive values. The skewness and kurtosis coefficients were at times relatively large. Afifi and Clark [1984, p 60] noted that not every distribution can be transformed to a normal distribution. For example, the mode (the most commonly occurring score) is zero for some positive value ratios, thus making it virtually impossible to transform their score to a normal distribution.

Table 6-2 Summary of the Distributional Evidence of Financial Ratios (Raw Data)

Study	No of Ratios	Period covered	Sample Size	Null Hypothesis (Normality)
Horrigan [1965], USA	7	1948-57	50	Not Rejected
O'Conner [1973], USA	10	1950-66	127	Not rejected
Deakin [1976], USA	11	1955-73	454-1114	Mixed
Frecka & Hopwood[1983] USA	11	1950-79	346-1243	Rejected
McDonald & Morris [1984, 85], USA	4	1979 239	Mixed	
Lee [1985], USA	5	1961,65,70, 75	348-606	Mixed
So [1987], USA	11	1970-79	490	Mixed
Karels & Prakash [1987]	50	1972-76	50	Rejected
Bird & McHugh [1977] Australia	5	1967,69,71	68	Mixed
Bougen & Druby [1980], UK	7	1975 700	Rejected	
Mcleay [1986],UK & Ireland	3	1981-82	1634	Rejected
Ezzamel, Mar-Molinero, and Beecher [1987], UK	5	1980-81	131	Mixed
Ezzamel, Mar-Molinero, [1990], UK	9	1973-81	0	Rejected

Source : Journal of Business Finance and Accounting, Spring [1990, p. 2].

For example, in this study, TC/TS, TC/TA and TC/CL (defined as in Appendix A) three ratios's mode is zero. The inverse of some ratios which are bounded by zero, were reported to be non-normally distributed by several previous researchers [e.g., Deakin, 1976; Frecka and Hopwood, 1983; and So, 1987;]. Hence, the results of previous studies and those of the present study indicate that these ratios exhibit non-normal distributions (see Table 6-2 to 6-7).

6.2.4. Descriptive Statistics

A general family of transformations for each distribution of ratios was applied. It can be seen that the normality of the data set was improved after it transformed and winsorized. [see Table 6-8]. The SAS / Univariate procedure was then used to procure descriptive statistics and to examine the histograms and normal probability plots of each ratio, and various statistics such as the mean, the sum, the standard deviation, the variance, skewness, kurtosis and the lowest and highest extremes were generated. The normality of a ratio depends on the shape of the histogram and normal probability plot, it is easy and convenient to test the goodness-of-fit on the basis of visual inspection (graphical tests). If the points fall on an appropriate straight line on the normal probability plot, this indicates the variable is following a normal distribution. The horizontal axis of a normal probability plot is the numbers between the -2 and +2, the vertical points are the coefficient correlation between the vertical and horizontal lines can also be used as an indication of goodness of fit. Otherwise, the plot line should curve in the interval.

The results of the initial data analysis can be classified into two parts: failed and non-failed. In general, the histograms of failed firms were less symmetric, compared with the non-failed sample. Overall, the skewness and kurtosis coefficient for the failed firms were fairly large, compared with non-failed firms. The distribution of failed companies' ratios departs increasingly from normality as the firms approach failure. WC/TA for the non-failed firms appears to be approximately bell-shaped. TL/TA for the failed firms appears to be approximately bell-shaped for the all 264 firms all years prior to failure (see Table 6-3).

6.2.5 Tests For Normality

There are two different methods used in this study to examine the normal distribution of each independent financial ratios, firstly the Shapiro-Wilk tests, secondly the skewness and kurtosis test.

6.2.5.1 Shapiro-Wilk (S-W) Tests

The Shapiro-Wilk (S-W) statistic, W, is computed if the number of observations is less than 2000. This test is well suited to small sample size (see Dunn and Clark 1987). The null hypothesis of normality is rejected for small values of W. An alternative is the Kolmogorov-Smirnov (K-S) test, however, this is not as powerful for small samples sizes as the Shapiro-Wilk (S-W) test (Afifi and Azen, 1979). With a sample size of three, the probability distribution of W is known and is used to determine the significance level. When the sample size is greater than three, simulation results are used to determine the significance levels. For sample size, n, greater than six, the significance level of W is obtained by Royston's [1982, p. 116] approximate normalizing transformation. The SAS program prints out the value of W and the associated probability (P value) for testing the hypothesis that the data came from a normal distribution. If the P value is small, then the data may not be normally distributed (see SAS procedure guide, version 6, 1990). The W statistic is the ratio of the best estimator of the variance (based on the square of a linear combination of the order statistics) to the usual corrected sum of squares estimator of the variance. W must be greater than zero and less than or equal to one, with small values of W leading to rejection of the null hypothesis of normality. Note that the distribution of W is highly skewed. Seemingly large values of W may be considered small and lead to rejection of the null hypothesis.

Very little is known about what significance level α should be chosen to compare with the P value obtained from formal tests of normality. So the sense of increased preciseness gained by performing a formal test over examining a plot is somewhat of an illusion. From the normal probability plot we can both decide whether the data are normally distributed or not [Afifi and Clark, 1990]. For example, in Table 6-3 to 6-7, the most probability value contained in the Column Prob<W is 0.0001. Since this value is close to 0, it indicates that the sample data are not from a normal distribution.

In this study, the S-W test was performed on each (1) the complete raw data set; (2) each year (four year) raw data prior to failure respectively, and (3) the square root, the logarithmic, and reciprocal transformations of the raw data sets; (i.e. after transformed and winsorized). The financial ratios of the failed and non-failed firms selected for the unadjusted ratios, followed the tests for normal distributions. The ratios for these firms indicated similar results to the unadjusted financial ratios. The power of the S-W test, (in common with most statistical tests), increases as the number of observations increases. Small samples cause more departures than large sample from normality and tenably reject the normality hypothesis.

6.2.5.2 Skewness and Kurtosis Tests

Skewness is a measure of the deviation of a distribution from symmetry, a negative sign indicates that the tail of their distribution is to the left and the distribution is skewed to the smaller value. If the sign is positive, the distribution would be skewed to the right. The kurtosis of a data set is sometimes examined to provide an informal check of normality; kurtosis of a normal distribution is zero. Kurtosis expresses a distributions relative peakedness. It is normally measured by β_2 (beta two) or by $\alpha 4$ (alpha 4). It is useful to identify distributions, which are symmetrical but not normal, because the greater the value of β_2, the more peaked the distribution. A normal distribution has a β_2 of three and is called mesokurtic. If the β_2 is greater than 3, the distribution is leptokurtic; and if β_2 is less than 3, the distribution is platykurtic. If both statistics differ significantly from zero, the normality of data set is not achievable. Using the tables in Pearson and Hartley [1976, pp. 207-8] the coefficients of skewness and kurtosis can provide test results similar to those for the Shapiro-Wilks.

From the Tables 6-3 to 6-7 displayed below, a number of ratios, particularly for the failed sample, appear to be non-normally distributed. This can be attributed to the fact that the distribution of failed companies ratios departs increasingly from the normal distribution when the failed firms approach failure. The distribution of non-failed firm's ratios from 16 UK industries, can be seen from the visual inspection of the Tables 6-3 to 6-7. These indicate that the mean, standard deviation, skewness, Kurtosis, W-statistics and significance figures for the non-failed firm ratios are more consistently near to normal compared with those of the failed firms. On the other hand, failed firm descriptive moments exhibit a great deal of non-normality prior to failure. The following results in Table 6-3 shows all-firms five years prior to failure. Table 6-4 to Table 6-7 show univariate analysis one, two, three, and four year prior to failure. Table 6-8 presents the improvement results of transformation for all year.

In summary, as stated above, forty-one accounting ratios which measure the same financial attributes for 16 broadly classified industries and for five years prior to failure are calculated separately. These ratios are examined jointly and separately using square roots, reciprocal, natural logarithms and Box and Cox [1964] family of transformations methods. The results of the, Shapiro-Wilk (W), Skewness and Kurtosis tests indicated that the normality assumption was rejected far more frequently in the failed than in the non-failed groups raw data sets (see Table 6-3 to 6-7 footnote). If the associated probabilities is labelled Prob<W for the Shapiro-Wilk test. If the value is less than the level then the null hypothesis is rejected. The significant results of the three different tests revealed that the normality assumption could not be rejected in most cases for WC/TA in the non-failed firms, and for TL/TA in the failed firms (see Table 6-3). The deletion of outliers had a stronger impact on the data, in terms of improving approximation to normality, than did square root and natural logarithmic transformations. Transforming data using the Box and Cox [1964] family of transformations generally improved the approximations to normality. The final transformations applied to the data were those which resulted in the greatest improvement. An examination of the figures in the Tables also shows that there is a close relationship between the two statistics in that those ratios with a low skewness also have a low kurtosis.

Table 6-3 Untransformed Ratio Distribution Statistics For the Non-Failed and Failed Firms (All Year)

Ratios	NON-FAILED Mean	Skew	Kurtosis	W: Normal	Prob<W	FAILED Mean	Skew	Kurtosis	W Normal	Prob<W
NI/TS	3.69	3.52	32.18	0.747	0.0001	-3.29	-18.69	372.22	0.179	0.0001
FF/NW	30.29	-3.15	53.72	0.865	0.0001	15.93	-1.63	7.17	0.882	0.0001
FF/TA	14.72	-0.85	18.03	0.944	0.0001	5.74	-2.13	12.32	0.897	0.0001
NI/TA	5.06	-6.29	117.12	0.771	0.0001	-2.14	-3.19	20.21	0.788	0.0001
NI/NW	10.20	-2.03	27.38	0.891	0.0001	-7.26	-3.37	28.92	0.710	0.0001
EBIT/TS	8.84	2.98	22.93	0.840	0.0001	1.11	-17.81	351.03	0.230	0.0001
NI/TL	14.91	3.23	25.15	0.791	0.0001	-3.43	-8.85	123.99	0.570	0.0001
EBIT/TA	12.55	-0.15	29.62	0.894	0.0001	3.31	-2.27	13.43	0.889	0.0001
QA/TA	0.33	0.29	0.88	0.975	0.0001	0.30	0.47	1.08	0.965	0.0001
FF/TS	0.10	-18.61	477.96	0.413	0.0001	0.03	-17.32	336.99	0.245	0.0001
CA/TA	0.67	-1.03	1.66	0.931	0.0001	0.66	-0.68	0.96	0.951	0.0001
NW/TS	0.42	12.50	184.84	0.282	0.0001	0.32	9.11	133.41	0.572	0.0001
TS/TA	1.65	2.86	13.25	0.775	0.0001	1.43	1.67	11.82	0.935	0.0001
WC/TA	0.29	-0.16	0.15	**0.985**	**[illegible]**	0.15	-1.23	4.41	0.940	0.0001
TS/NPA	7.67	10.96	149.85	0.329	0.0001	7.56	6.82	55.37	0.390	0.0001
TL/TA	50.68	0.54	1.54	0.969	0.0001	64.80	0.64	2.95	**0.981**	**0.3900**
TL/NW	113.7	1.40	2.25	0.881	0.0001	200.38	0.24	10.13	0.827	0.0001
LTD/CA	11.17	7.81	85.77	0.447	0.0001	22.86	7.34	75.13	0.433	0.0001
CG	20.48	0.77	0.62	0.931	0.0001	42.59	-0.86	12.95	0.944	0.0001
FF/CL	44.12	1.44	5.31	0.915	0.0001	12.11	-3.64	38.08	0.785	0.0001
RE/TA	4.09	-5.64	91.35	0.781	0.0001	-3.57	-5.28	55.08	0.699	0.0001
TD/TC	83.79	1.87	4.84	0.840	0.0001	171.30	0.22	12.99	0.798	0.0001
TD/TA	43.07	0.83	2.08	0.959	0.0001	61.38	2.42	16.29	0.873	0.0001
CA/CL	1.93	1.80	6.09	0.879	0.0001	1.40	2.45	15.09	0.874	0.0001
QA/CL	0.98	2.11	8.58	0.854	0.0001	0.65	6.28	75.48	0.702	0.0001
CL/NW	0.86	2.32	8.91	0.817	0.0001	1.38	-13.22	282.36	0.157	0.0001
CL/TA	0.38	0.56	0.84	0.969	0.0001	0.52	1.85	10.73	0.908	0.0001
CL/TL	0.76	-0.48	-0.13	0.963	0.0001	0.80	-1.12	1.92	0.913	0.0001
*TC/TS	0.06	13.36	228.09	0.314	0.0001	0.02	10.16	119.33	0.250	0.0001
*TC/TA	0.07	2.23	6.28	0.718	0.0001	0.02	6.40	66.43	0.500	0.0001
*TC/CL	0.24	3.22	14.95	0.631	0.0001	0.07	13.67	225.30	0.228	0.0001
CA/TS	0.46	5.44	54.81	0.689	0.0001	0.51	3.02	14.16	0.763	0.0001
INV/TS	0.23	3.26	17.42	0.750	0.0001	0.28	4.47	31.72	0.688	0.0001
TS/WC	8.69	6.50	101.76	0.393	0.0001	3.09	-3.67	33.83	0.580	0.0001
QA/INV	2.52	16.03	296.08	0.142	0.0001	1.24	12.70	175.33	0.228	0.0001
QA/TS	0.23	10.96	177.11	0.509	0.0001	0.23	4.46	31.90	0.691	0.0001
QA/TL	0.72	1.69	5.43	0.886	0.0001	0.51	9.41	139.86	0.579	0.0001
IC/TS	0.01	4.10	24.61	0.610	0.0001	0.03	5.80	60.37	0.658	0.0001
Log(TA)	17350	5.91	47.84	0.485	0.0001	18044	3.40	13.34	0.601	0.0001
OP/TP	2.40	6.20	88.91	0.630	0.0001	1.77	-3.02	64.68	0.455	0.0001
IC	15.54	5.91	79.17	0.463	0.0001	15.15	-3.34	53.48	0.467	0.0001

Note:

* Means mode = 0,

W = Shapiro Wilk Statistic,

Prob<W = Associated probabilities, for testing the hypothesis that the data come from a normal distribution.

W:Normal, test statistics. With small values of W leading to rejection of the null hypothesis of normality (see Royston, 1982)

Definitions of these ratios are given in Appendix A.

Table 6-4 Untransformed Ratio Distribution Statistics For the Non-Failed and Failed Firms (Year -1)

Ratios	NON-FAILED Mean	Skew	Kurtosis	W: Normal	Prob<W	FAILED Mean	Skew	Kurtosis	W Normal	Prob<W
NI/TS	3.22	5.10	45.96	0.712	0.0001	-14.79	-9.09	84.23	0.19	0.0001
FF/NW	25.51	0.37	0.90	0.983	0.5010	-6.19	-0.85	3.65	0.90	0.0001
FF/TA	13.07	2.01	16.18	0.895	0.0001	-2.54	-3.06	16.56	0.795	0.0001
NI/TA	4.29	1.97	14.75	0.878	0.0001	-10.27	-3.59	20.24	0.737	0.0001
NI/NW	7.96	-0.15	2.98	0.973	0.0769	-35.43	-1.77	4.45	0.863	0.0001
EBIT/TS	7.87	1.77	7.05	0.900	0.0001	-10.42	-8.71	80.01	0.230	0.0001
NI/TL	12.35	3.53	22.22	0.761	0.0001	-17.63	-7.42	63.04	0.390	0.0001
EBIT/TA	10.97	4.14	36.99	0.770	0.0001	-5.38	-3.13	17.64	0.797	0.0001
QA/TA	0.33	0.12	0.97	0.984	0.6880	0.29	0.68	1.96	0.947	0.0035
FF/TS	0.09	1.29	3.14	0.918	0.0001	-0.09	-8.53	77.45	0.244	0.0001
CA/TA	0.66	-0.94	0.93	0.929	0.0001	0.64	-0.60	0.66	0.957	0.0218
NW/TS	0.45	10.78	131.26	0.317	0.0001	0.30	7.60	65.66	0.374	0.0001
TS/TA	1.66	3.14	13.87	0.731	0.0001	1.43	0.16	0.29	0.979	0.0001
WC/TA	0.29	-0.27	0.24	0.984	0.6750	0.05	-1.41	6.93	0.929	0.0001
TS/NPA	7.19	5.76	47.77	0.584	0.0001	6.76	3.88	18.21	0.577	0.0001
TL/TA	47.87	0.63	1.60	0.973	0.0911	72.47	0.30	1.92	0.984	0.7735
TL/NW	103.39	1.25	1.25	0.878	0.0001	293.74	1.12	1.31	0.893	0.0001
LTD/CA	10.55	5.29	41.08	0.572	0.0001	24.52	4.30	21.41	0.534	0.0001
C.G	19.91	0.79	0.56	0.927	0.0001	53.99	0.38	0.21	0.978	0.4811
FF/CL	39.13	2.60	15.00	0.852	0.0001	-6.31	-3.93	32.62	0.601	0.0001
RE/TA	3.42	-0.25	5.32	0.919	0.0001	-13.70	-2.45	9.72	0.821	0.0001
TD/TC	82.43	1.52	2.61	0.866	0.0001	254.60	1.44	3.12	0.871	0.0001
TD/TA	42.63	0.81	2.03	0.966	0.0098	70.84	3.82	26.78	0.747	0.0001
CA/CL	1.93	1.24	1.82	0.905	0.0001	1.15	1.05	2.14	0.942	0.0012
QA/CL	0.99	1.59	4.06	0.886	0.0001	0.53	4.06	26.04	0.715	0.0001
CL/NW	0.81	1.35	1.94	0.887	0.0001	4.00	7.69	62.94	0.244	0.0001
CL/TA	0.38	0.56	0.74	0.976	0.1877	0.60	2.29	14.14	0.862	0.0013
CL/TL	0.80	-0.81	0.85	0.952	0.0001	0.82	-1.42	2.96	0.874	0.0001
*TC/TS	0.07	10.46	124.26	0.286	0.0001	0.03	6.97	52.54	0.235	0.0001
*TC/TA	0.07	1.67	2.19	0.737	0.0001	0.02	4.59	24.15	0.452	0.0001
*TC/CL	0.27	2.75	8.98	0.639	0.0001	0.05	8.40	74.78	0.222	0.0001
CA/TS	0.49	5.48	42.43	0.559	0.0001	0.52	2.49	7.02	0.733	0.0001
INV/TS	0.24	3.87	21.64	0.692	0.0001	0.27	3.23	17.53	0.778	0.0001
TS/WC	9.28	8.35	87.27	0.369	0.0001	-8.61	-2.09	9.67	0.727	0.0001
QA/INV	1.87	10.33	120.41	0.272	0.0001	1.59	8.87	81.38	0.222	0.0001
QA/TS	0.25	9.59	111.45	0.412	0.0001	0.25	4.23	20.69	0.557	0.0001
QA/TL	0.79	1.84	5.82	0.874	0.0001	0.42	0.27	0.53	0.977	0.4343
IC/TS	0.01	3.98	22.74	0.631	0.0001	0.05	5.42	38.20	0.550	0.0001
Log(TA)	21222	5.43	39.94	0.524	0.0001	18481	3.24	12.15	0.628	0.0001
OP/TP	2.33	-0.72	15.45	0.818	0.0001	0.91	-3.11	22.61	0.666	0.0001
IC	15.66	5.47	52.23	0.567	0.0001	14.44	-5.81	47.29	0.484	0.0001

Table 6-5 Untransformed Ratio Distribution Statistics For the Non-Failed and Failed Firms (Year -2)

	NON-FAILED					FAILED				
Ratios	Mean	Skew	Kurtosis	W: Normal	Prob<W	Mean	Skew	Kurtosis	W Normal	Prob<W
NI/TS	3.62	4.62	36.89	.724	.0001	-2.95	-4.31	25.00	.607	.0001
FF/NW	28.74	0.34	0.87	.982	.5178	11.25	-1.72	6.05	.837	.0001
FF/TA	14.24	0.50	5.57	.966	.0103	3.96	-1.05	1.46	.919	.0001
NI/TA	4.85	0.42	1.96	.970	.0350	-1.10	-2.10	5.43	.800	.0001
NI/NW	9.50	0.25	2.03	.971	.0515	-8.97	-2.84	10.46	.721	.0001
EBIT/TS	8.60	1.62	4.46	.893	.0001	1.63	-1.09	8.33	.863	.0001
NI/TL	13.58	1.62	4.26	.885	.0001	-5.41	-4.51	29.40	.653	.0001
EBIT/TA	12.22	2.65	18.31	.872	.0001	1.93	-1.14	1.54	.914	.0001
QA/TA	0.33	0.23	0.66	.984	.6957	0.31	0.38	1.31	.983	.7245
FF/TS	0.08	-11.98	153.91	.247	.0001	0.03	-0.94	6.83	.870	.0001
CA/TA	0.67	-0.98	1.35	.939	.0001	0.67	-0.59	0.93	.946	.0032
NW/TS	0.45	12.08	154.78	.233	.0001	0.33	2.55	18.26	.796	.0001
TS/TA	1.65	2.92	13.50	.780	.0001	1.32	0.17	1.09	.990	.9627
WC/TA	0.29	0.07	-0.06	.984	.6606	0.15	-2.23	11.52	.866	.0001
TS/NPA	7.29	8.23	87.26	.452	.0001	7.41	5.58	37.18	.432	.0001
TL/TA	49.47	0.45	1.08	.978	.2711	64.00	0.38	2.18	.978	.4849
TL/NW	108.22	1.58	3.54	.876	.0001	197.11	1.51	4.10	.876	.0001
*LTD/CA	10.92	7.13	67.81	.471	.0001	22.74	4.40	24.22	.562	.0001
*C.G	19.94	0.65	-0.11	.932	.0001	41.10	-4.00	27.03	.736	.0001
FF/CL	42.26	1.46	3.19	.895	.0001	[illegible]	-4.35	29.80	.692	.0001
RE/TA	3.96	-0.19	1.89	.980	.3643	-5.76	-6.41	50.85	.482	.0001
TD/TC	83.18	1.74	4.25	.856	.0001	168.80	0.82	2.52	.926	.0001
TD/TA	42.89	0.61	0.89	.969	.0250	62.46	3.69	25.09	.757	.0001
CA/CL	1.93	1.18	1.35	.902	.0001	1.40	5.02	37.33	.646	.0001
QA/CL	0.98	1.83	5.98	.878	.0001	0.69	7.20	60.52	.432	.0001
CL/NW	0.83	2.00	6.07	.844	.0001	1.50	0.71	1.33	.923	.0001
CL/TA	0.38	0.40	0.35	.983	.0001	0.52	3.27	21.27	.792	.0001
CL/TL	0.78	-0.55	-0.09	.950	.0001	0.81	-1.10	2.13	.915	.0001
*TC/TS	0.07	10.64	127.43	.278	.0001	0.03	8.51	76.32	.234	.0001
*TC/TA	0.07	1.97	4.28	.739	.0001	0.03	5.60	37.95	.414	.0001
*TC/CL	0.26	3.39	16.17	.628	.0001	0.13	8.17	70.84	.213	.0001
CA/TS	0.48	5.53	44.49	.613	.0001	0.55	3.39	17.26	.725	.0001
INV/TS	0.24	3.60	18.48	.703	.0001	0.30	5.01	35.13	.628	.0001
TS/WC	9.40	5.93	42.12	.427	.0001	7.82	4.12	31.89	.640	.0001
QA/INV	1.71	6.07	43.41	.434	.0001	1.49	8.81	80.38	.226	.0001
QA/TS	0.24	9.57	111.38	.420	.0001	0.25	4.72	34.48	.676	.0001
QA/TL	0.74	1.58	4.18	.891	.0001	0.56	7.94	69.87	.365	.0001
IC/TS	0.01	4.29	24.49	.582	.0001	0.04	2.84	12.69	.777	.0001
Log(TA)	19483	5.83	46.18	.505	.0001	20905	3.27	12.12	.611	.0001
OP/TP	2.37	1.64	8.47	.881	.0001	1.14	-5.34	44.64	.520	.0001
IC	15.57	5.35	70.20	.463	.0001	15.29	-0.50	17.25	.715	.0001

Table 6-6 Untransformed Ratio Distribution Statistics For the Non-Failed and Failed Firms (Year - 3)

Ratios	NON-FAILED					FAILED				
	Mean	Skew	Kurtosis	W: Normal	Prob<W	Mean	Skew	Kurtosis	W Normal	Prob<W
NI/TS	3.69	4.97	42.01	0.70	.0001	-0.21	-2.74	9.72	0.69	.0001
FF/NW	30.80	0.81	1.25	0.95	.0001	24.04	0.38	2.03	0.97	.2187
FF/TA	14.71	0.30	0.70	0.98	.6770	8.59	-0.93	1.45	0.94	.0027
NI/TA	5.09	0.59	1.54	0.97	.0622	0.56	-2.45	9.48	0.79	.0001
NI/NW	10.48	0.96	2.79	0.94	.0001	4.02	0.77	17.35	0.74	.0001
EBIT/TS	8.68	1.69	5.80	0.89	.0001	4.16	-0.72	3.38	0.90	.0001
NI/TL	14.85	2.47	9.98	0.81	.0001	0.74	-2.40	7.44	0.76	.0001
EBIT/TA	12.45	0.55	1.23	0.98	.5617	6.26	-1.06	1.53	0.92	.0001
QA/TA	0.32	0.43	1.17	0.97	.2624	0.30	0.25	0.18	0.97	.1546
FF/TS	0.09	1.29	3.85	0.92	.0001	0.05	-0.37	2.57	0.93	.0009
CA/TA	0.67	-1.17	2.03	0.91	.0001	0.67	-0.95	2.11	0.94	.0021
NW/TS	0.41	11.01	136.0	0.31	.0001	0.33	1.50	4.05	0.90	.0001
TS/TA	1.64	2.30	8.88	0.82	.0001	1.47	3.55	23.56	0.77	.0001
WC/TA	0.29	-0.26	-0.17	0.97	.1235	0.18	-0.96	2.87	0.95	.0310
TS/NPA	8.06	10.62	127.5	0.29	.0001	8.12	6.10	51.73	0.38	.0001
TL/TA	50.75	0.50	1.18	0.97	.2303	61.47	0.87	3.13	0.95	.0190
TL/NW	115.2	1.62	3.37	0.86	.0001	157.67	-2.15	20.27	0.73	.0001
*LTD/CA	12.20	8.21	82.84	0.37	.0001	24.52	8.10	70.70	0.29	.0001
*C.G	20.69	0.60	-0.04	0.93	.0001	40.13	1.37	4.73	0.92	.0001
FF/CL	44.04	1.22	2.75	0.93	.0001	18.03	-0.80	1.84	0.94	.0042
RE/TA	4.24	-0.58	5.82	0.95	.0002	0.17	-1.46	4.59	0.89	.0001
TD/TC	83.54	2.03	6.16	0.83	.0001	136.82	-2.06	21.76	0.69	.0001
TD/TA	42.87	0.84	2.22	0.96	.0068	57.99	1.05	3.17	0.94	.0035
CA/CL	1.94	1.84	6.47	0.88	.0001	1.47	1.08	2.64	0.93	.0001
QA/CL	0.95	2.58	11.83	0.82	.0001	0.67	0.96	3.55	0.94	.0058
CL/NW	0.86	2.13	6.45	0.82	.0001	1.22	-2.85	25.56	0.68	.0001
CL/TA	0.37	0.54	0.83	0.97	.1824	0.49	1.62	5.53	0.89	.0001
CL/TL	0.75	-0.43	-0.32	0.95	.0001	0.78	-0.09	1.39	0.93	.0003
*TC/TS	0.04	4.62	33.10	0.60	.0001	0.01	2.81	9.31	0.60	.0001
*TC/TA	0.06	2.60	9.74	0.71	.0001	0.02	2.20	4.13	0.63	.0001
*TC/CL	0.22	4.48	30.62	0.59	.0001	0.05	3.97	18.79	0.51	.0001
CA/TS	0.45	1.27	3.41	0.92	.0001	0.50	3.75	23.24	0.74	.0001
INV/TS	0.23	1.99	7.33	0.86	.0001	0.28	5.04	35.91	0.63	.0001
TS/WC	7.58	-0.86	40.41	0.47	.0001	2.83	-7.51	63.71	0.37	.0001
QA/INV	1.77	6.79	52.90	0.35	.0001	1.08	3.14	12.63	0.69	.0001
QA/TS	0.22	2.00	8.12	0.87	.0001	0.22	0.25	0.77	0.98	.6049
QA/TL	0.70	1.77	6.46	0.89	.0001	0.52	1.98	10.40	0.88	.0001
IC/TS	0.01	4.86	31.85	0.55	.0001	0.02	2.94	14.51	0.76	.0001
Log(TA)	15877	3.30	13.24	0.63	.0001	18430	3.33	13.19	0.61	.0001
OP/TP	2.35	0.21	10.72	0.80	.0001	3.08	6.01	47.06	0.43	.0001
IC	15.46	-1.40	32.47	0.60	.0001	16.24	1.53	25.92	0.48	.0001

Table 6-7 Untransformed Ratio Distribution Statistics For the Non-Failed and Failed Firms (Year - 4)

Ratios	NON_FAILED Mean	Skew	Kurtosis	W: Normal	Prob<W	FAILED Mean	Skew	Kurtosis	W Normal	Prob<W
NI/TS	3.70	1.03	19.88	0.80	.0001	0.88	-1.48	3.94	0.88	.0001
FF/NW	31.36	-5.76	60.34	0.66	.0001	24.80	-2.67	16.51	0.82	.0001
FF/TA	15.14	-3.84	33.24	0.80	.0001	9.71	-0.75	0.17	0.93	.0004
NI/TA	4.99	-7.70	83.46	0.53	.0001	1.34	-1.84	5.53	0.86	.0001
NI/NW	10.53	-4.01	31.28	0.74	.0001	-0.33	-7.26	60.26	0.39	.0001
EBIT/TS	9.16	3.24	27.33	0.81	.0001	5.25	-0.36	2.01	0.97	.4561
NI/TL	15.98	1.91	15.64	0.83	.0001	2.78	-1.54	4.22	0.89	.0001
EBIT/TA	12.87	-4.50	41.50	0.75	.0001	7.31	-0.83	0.74	0.93	.0005
QA/TA	0.33	0.38	1.09	0.98	.3850	0.29	0.46	1.32	0.96	.1713
FF/TS	0.10	0.56	4.38	0.95	.0006	0.07	-0.21	0.69	0.98	9244
CA/TA	0.67	-1.10	2.20	0.93	.0001	0.66	-0.71	0.97	0.96	0513
NW/TS	0.38	10.15	121.0	0.37	.0001	0.32	1.86	5.97	0.87	.0001
TS/TA	1.68	2.55	10.40	0.80	.0001	1.46	1.41	5.93	0.93	.0004
WC/TA	0.28	-0.33	0.74	0.98	.7493	0.17	-0.57	0.28	0.96	.0703
TS/NPA	8.22	10.64	127.9	0.28	.0001	7.70	7.66	64.55	0.34	.0001
TL/TA	52.22	0.72	2.54	0.96	.0007	62.53	1.37	6.98	0.93	.0001
TL/NW	119.3	1.35	1.88	0.88	.0001	179.55	1.84	3.93	0.82	.0001
*LTD/CA	10.97	8.54	91.64	0.41	.0001	21.17	4.97	27.87	0.45	.0001
*C G	20.75	1.02	1.72	0.91	.0001	38.37	0.02	-0.53	0.96	.1192
FF/CL	45.90	0.64	4.79	0.94	.0001	21.04	-0.51	2.13	0.97	5729
RE/TA	3.94	-7.86	82.68	0.51	.0001	1.61	0.70	10.53	0.84	0001
TD/TC	85.01	2.10	6.01	0.81	.0001	157.98	2.76	9.47	0.72	.0001
TD/TA	43.24	1.17	3.61	0.94	.0001	57.81	1.40	5.83	0.93	0002
CA/CL	1.94	2.31	11.14	0.86	.0001	1.47	1.08	1.82	0.92	.0001
QA/CL	0.97	2.63	13.49	0.83	.0001	0.67	0.62	0.94	0.96	1548
CL/NW	0.89	1.68	2.77	0.82	.0001	1.52	4.31	25.10	0.62	.0001
CL/TA	0.38	0.66	0.86	0.96	.0057	0.48	0.31	-0.32	0.96	1339
CL/TL	0.73	-0.41	0.10	0.96	.0180	0.79	-1.05	1.59	0.92	.0001
*TC/TS	0.04	3.35	17.43	0.65	.0001	0.02	4.12	21.84	0.54	.0001
*TC/TA	0.06	2.58	9.64	0.71	.0001	0.02	2.12	4.51	0.67	0001
*TC/CL	0.22	2.95	11.30	0.64	.0001	0.05	2.64	7.24	0.61	.0001
CA/TS	0.44	1.59	6.38	0.91	.0001	0.49	2.29	9.36	9.36	.0001
INV/TS	0.23	2.66	11.42	0.79	.0001	0.27	3.38	18.55	0.76	.0001
TS/WC	7.79	5.94	80.05	0.35	.0001	8.54	1.85	7.05	0.78	0001
QA/INV	2.97	11.47	140.7	0.16	.0001	1.03	2.64	7.96	0.71	.0001
QA/TS	0.21	1.19	3.81	0.94	.0001	0.21	1.03	1.81	0.93	.0002
QA/TL	0.68	1.58	4.82	0.90	.0001	0.52	1.35	4.05	0.92	0001
IC/TS	0.01	3.26	15.49	0.67	.0001	0.02	1.46	2.58	0.86	.0001
Log(TA)	14031	3.47	14.52	0.61	.0001	16775	3.62	15.67	0.59	.0001
OP/TP	2.48	7.93	79.22	0.42	.0001	2.81	6.71	54.88	0.41	.0001
IC	15.49	6.74	77.46	0.42	.0001	15.94	5.06	41.47	0.47	.0001

Table 6-8 Improvement Results of Transformation For All Years

Ratios	Winsorised	Transformation Power	Results Improvement Non-failed (B) W	(A) W	Failed (B) W	(A) W
(1)	(2)	(3)	(4)	(5)	(6)	(7)
NI/TS	YES	SQRT	.747	.979	.179	.968
FF/NW	No	SQRT	.865	.983	.882	.964
FF/TA	YES	SQRT	.944	.965	.897	.966
NI/TA	YES	SQRT	.771	.978	.788	.948
NI/NW	NO	SQRT	.891	.987	.710	.846
EBIT/TS	YES	SQRT	.840	.978	.230	.973
NI/TL	YES	SQRT	.791	.964	.570	.970
EBIT/TA	YES	SQRT	.894	.974	.889	.967
QA/TA	NO	NONE	.975	.977	.965	.972
FF/TS	YES	SQRT	.413	.977	.245	.960
CA/TA	YES	λ_2=.5 λ_1 =2	.931	.963	.951	.964
NW/TS	YES	λ_2=.7 λ_1 =.1	.282	.932	.572	.859
TS/TA	YES	λ_2=.5 λ_1 =.2	.775	.959	.935	.976
WC/TA	NO	NONE	.985	.985	.940	.940
TS/NPA	YES	λ_2=.5 λ_1=.1	.329	.967	.390	.965
TL/TA	YES	NONE	.969	.977	.971	.960
TL/NW	NO	LOG	.881	.982	.827	.983
LTD/CA	YES	SQRT	.447	.910	.433	.931
C.G	YES	λ_2=1 λ_1=.8	.931	.943	.944	.897
FF/CL	YES	λ_2=33 λ_1=.5	.915	.976	.785	.900
RE/TA	YES	SQRT	.781	.976	.699	.965
TD/TC	NO	LOG	.840	.985	.798	.985
TD/TA	YES	NONE	.959	.973	.873	.948
CA/CL	YES	SQRT	.879	.954	.874	.973
QA/CL	YES	λ2=0 λ1=.5	.854	.963	.702	.974
CL/NW	YES	SQRT	.817	.959	.157	.934
CL/TA	YES	λ_2=0 λ_1=0.8	.969	.978	.908	.942
CL/TL	NO	λ_2=0 λ_1=1.8	.963	.968	.913	.948
TC/TS	YES	1/(.9+TC/TS)	.314	.843	.250	.694
TC/TA	NO	LOG	.718	.840	.500	.701
TC/CL	NO	LOG	.631	.848	.228	.661
CA/TS	YES	λ_2 =0 λ_1 =.8	.689	.932	.763	.881
INV/TS	YES	λ_2=.1 λ_1=.8	.750	.927	.688	.951
TS/WC	NO	LOG	.393	.948	.580	.981
QA/INV	YES	LOG	.142	.916	.228	.865
QA/TS	YES	λ_2=0 λ_1=0.7	.509	.961	.691	.934
QA/TL	NO	λ_2=0 λ_1=0.5	.886	.967	.579	.900
IC/TS	YES	LOG	.610	.821	.658	.947
Log(TA)	NO	LOG	.485	.978	.601	.974
OP/TP	YES	LOG	.630	.967	.455	.960
IC	YES	LOG	.463	.933	.467	.969

Note:
Col 4, 6 Result for NF & F firms before adjustment.
Col 5, 7 Result for NF & F firms after adjustment
W = Shapiro-Wilk Statistic [see chapter 6-2-5-1].
B = Before Adjustment A = After Adjustment.
Key to transformation: Log = logarithm; SQRT = Square root; λ_2 = Constant λ_1 = transformation parameter.

6-3 Correlation Analysis

Correlation is a measure of the relationship between two variables. If one variable x can be expressed exactly as a linear function of another variable y, then the correlation is 1, (if the variables are directly related), or -1 (if the variables are inversely related). If the values are normally distributed, then a correlation of 0 means that the variables are linearly independent of one another. The Pearson Product moment correlation coefficient r is a measure of the strength of the linear relationship between two variables x and y. A value of r near or equal to 0 implies little or no linear relationship between the values of y and x that were observed in the sample. In contrast, the closer r is to 1 or -1, the stronger the linear relationship between x and y. And, if r = 1 or r = -1, all the points fall exactly on the least squares line. Positive values of r imply that y increases as x increases; negative values imply that y decreases as x increases. Prior to developing prediction of failure models by applying MDA, the forty-one variables were analysed for inter-correlation. Correlation coefficients computed from the pooled covariance matrix above 0.6 are investigated, because values higher than this are considered highly correlated. The results indicate that many of the pairs of the 41 variables selected for this study are highly correlated.

One indicator of the strength of the relationship among variables is the partial correlation coefficient. If the variables share common factors, the partial correlation coefficients between pairs of variables should be small when the linear effects of the other variables are eliminated. The partial correlations are then estimates of the correlations between the unique factors and should be close to zero when the factor analysis assumptions are met (Unique factors are assumed to be uncorrected with each other). The low correlations for the accounting ratios tends to support the conclusions reached by Pinches, Eubank, Mingo, and Carthers [1975] and by Chen and Shimerda [1981]. As briefly mentioned, their studies developed a set of ratios which had high factor loadings and low correlations. Profitability ratios, (for example, which had high factor loadings and low correlations. Profitability ratios, (for example, NI/TS and EBIT/TS) are very highly correlated. The implication is that positive linear relationships exist between NI/TS and EBIT/TS. This indicates that the two variables involved are related to each other, or overlap in what they measure. If the correlations between variables are small, it is unlikely that they share common factors.

Jackendoff [1962] demonstrates this overlapping and states that

> "Another type of redundancy arises from the use of ratios which are easily derived from one another, although the components are not identical as is true in inversions".

Overlapping can be found in most of the recent studies. For example, the 56 items in the computation of the 28 items included in the Elam [1975] study are derived from only 18 different pieces of financial data, and the 28 items for Deakin's [1972] ratio consist of only 10 separate pieces of data. Inclusion of more than one ratio from a factor leads to multicollinearity among ratios and distorts the relationship between the dependent and independent variables. Chen and Shimerda [1981] investigated many previous predictive studies of bankruptcy and demonstrated that high correlation between ratios causes results to be sample-sensitive and possibly misleading. It is important to select one ratio to represent each category for the sake of avoiding the collinearity problem and assisting in development of a useful set of financial ratios.

6-4 Empirical Univariate Analysis Results

6-4-1 The T-Test of Significance

The significance of the difference between the means of the failed and non-failed firms for each ratio, and for every year, was tested by the hypothesis that the true means are the same. This analysis can be considered a special case of a one-way analysis of variance with two levels of classification. The SAS T-Test computes the t statistic based on the assumption that the variances of two groups are equal, and it computes an approximate t based on the assumption that the variances are unequal. For each t, the degrees of freedom and probability level are given; Satterthwaite's [1946] approximation is used to compute the degrees of freedom associated with the approximate t. Under the assumption of unequal variances, the approximate t statistic is computed as

$$t' = (\bar{x}_1 - \bar{x}_2) \;/\; \sqrt{W_1 + W_2}$$

Where

$W_1 = s_1^2 / n_1$, $W_2 = s_2^2 / n_2$

$\bar{x}_1$ and $\bar{x}_2$ = means from two independent samples

n_1 = Observation 1

n_2 = Observation 2

s_1^2 and s_2^2 = the sample variances of the two groups.

The use of this t statistic depends on the assumption that $\sigma_1^2 = \sigma_2^2$, where σ_1^2 and σ_2^2 are the population variances of the two groups. The formula for Satterthwaite's approximation for the degrees of freedom for the approximate t statistic is as follows: [SAS 6.03].

$$df = \frac{(W_1 + W_2)^2}{W_1^2 / (n_1 - 1) + W_2^2 / (n_2 - 1)}$$

Refer to Steel and Torrie [1980], Freund, Littell, and Spector[1986] or SAS 6.03 [1990] for more information. However, an approximation to t may be computed. T, an approximate t statistic for testing the null hypothesis that the means of the two groups are equal. Prob > |T|, the probability of a greater absolute value of t under the null hypothesis. All the computations have been made by the SAS subprogram two-tailed T-Test procedure. Table 6-9 indicates that most ratios' means differed significantly between the failed and non-failed firms.

Table 6-9 Comparing the Differences Between Failed and Non-failed Groups Means.

Ratio	Prob> |T| -Year1	Prob> |T| -Year2	Prob> |T| -Year3	Prob> |T| -Year4	Prob> |T| -Year5
NI/TS	0.018	0.000	0.000	0.000	0.000
FF/NW	0.000	0.000	0.018	0.142	0.031
FF/TA	0.000	0.000	0.057	0.000	0.000
NI/TA	0.000	0.000	0.000	0.000	0.000
NI/NW	0.000	0.000	0.011	0.045	0.094
EBIT/TS	0.018	0.000	0.000	0.0007	0.000
NI/TL	0.000	0.000	0.000	0.000	0.000
EBIT/TA	0.000	0.000	0.000	0.000	0.000
QA/TA	0.009	0.128	0.133	0.024	0.014
FF/TS	0.018	0.013	0.000	0.000	0.000
CA/TA	0.325	0.973	0.810	0.800	0.662
NW/TS	0.075	0.081	0.119	0.163	0.194
TS/TA	0.010	0.000	0.081	0.009	0.003
WC/TA	0.000	0.000	0.000	0.000	0.000
TS/NPA	0.687	0.937	0.939	0.822	0.944
TL/TA	0.000	0.000	0.000	0.000	0.000
TL/NW	0.000	0.000	0.011	0.000	0.025
LTD/CA	0.003	0.009	0.150	0.049	0.000
CF/TD	0.000	0.000	0.000	0.000	0.000
FF/CL	0.000	0.000	0.000	0.000	0.000
RE/TA	0.000	0.000	0.000	0.050	0.000
TD/TC	0.000	0.000	0.001	0.000	0.015
TD/TA	0.000	0.000	0.000	0.000	0.000
CA/CL	0.000	0.000	0.000	0.000	0.000
QA/CL	0.000	0.000	0.000	0.000	0.000
CL/NW	0.017	0.000	0.015	0.000	0.397
CL/TA	0.000	0.000	0.000	0.000	0.000
CL/TL	0.336	0.086	0.023	0.012	0.108
TC/TS	0.113	0.096	0.000	0.000	0.008
TC/TA	0.000	0.000	0.000	0.000	0.001
TC/CL	0.000	0.091	0.000	0.000	0.000
CA/TS	0.378	0.087	0.044	0.059	0.054
INV/TS	0.194	0.042	0.043	0.045	0.035
TS/WC	0.002	0.552	0.173	0.946	0.083
QA/INV	0.653	0.679	0.016	0.075	0.068
QA/TS	0.995	0.845	0.801	0.929	0.655
QA/TL	0.000	0.017	0.000	0.000	0.000
TIC/TS	0.000	0.000	0.000	0.000	0.000
LOG(TA)	0.457	0.726	0.790	0.632	0.494
OP/TP	0.000	0.212	0.357	0.604	0.139
IC	0.019	0.680	0.386	0.470	0.155

If any one of above probabilities is less than a selected value α, 0.05, the null hypothesis, Ho: $\sigma_1 = \sigma_2$, is rejected, i.e., the difference between the two population means is significant at the 5% level.

6-4-2 Univariate Analysis (Profile Analysis)

Beaver [1966] was the first to use univariate analysis in his failure prediction model. The technique involves a graphic comparison between the mean values of two groups of companies for each ratios. Univariate analysis results are briefly discussed to aid future researcher in comparing the performance of failed and non-failed companies according to single financial ratios with similar studies. However, it could be argued that failure is a multidimensional concept which is unlikely to be fully reflected in a single ratio. Hence in the chapter 7-9 the technique of MDA is used to test whether selected combinations of ratios provide better predictive ability. There were two prime objectives in using univariate analysis of ratios in this study.

1. To evaluate and assess the possibilities of univariate analysis via the visual inspection of profiles to identify the characteristics between the means of failed and non-failed firms;

2. To identify whether these financial ratios are stable over 12 year span and across 16 industries.

It does not attempt to use univariate analysis for direct failure prediction since it will become clear that no individual ratio, nor any easily derivable statistic drawn from that ratio, completely distinguishes between failed and non-failed firms. Figure 6-1 presents a plot of the mean values of the 42 selected ratios for the failed and non-failed firms for five years prior to failure. R32 is excluded because of incomplete data. The difference in the mean values is in the predicted direction (see below) for the ratios in all five years before failure. The relative deterioration in the means of the failed firms is very noticeable over the five year period. The deviation from the trend line for non-failed firms is more consistent over the five years compared to failed firms. Since the control groups were matched samples, statements can be made about differences between failed and non-failed firms at specified times prior to failure, but are about failed and non-failed firms at particular points in time. An analysis comparing each year's results indicates few consistent differences among failed and non-failed firms. The difference in means between the failed and non-failed firms is evident for at least three years (year 1, year 2, and year 3) prior to failure, with the difference increasing as the year of failure approaches. Univariate analysis has the advantage of showing the difference in the mean values in the expected direction for the majority of ratios between the two groups. The differences displayed by univariate analysis should be considered together with their significance as measured by the t-test. A great many comparisons can be made using Figure 6-1, but only the most significant points will be highlighted here:

1. Profitability Ratios:

The profiles of all profitability ratios exhibit significant differences between the means of the failed and non-failed firms throughout the three year period prior to failure. Figure 6-1 shows the profitability of the failed firms to be strongly negative over the four year period before failure, but NI/NW showed a little rising trend and then declined again particularly in year three. Beaver [1966], Deakin [1972] and Libby's [1975] profile of the NI/TA showed it to be an obvious choice to discriminate between failed and non-failed firms. EBIT/TS ratio indicates the changes in overall operating profit margins from year to year. If the ratio is low, it may be because costs are too high for the income being generated. If the ratio is high, it could be due to efficient management or otherwise due to the company having a monopoly profit. The means of the non-failed firms were higher than for the failed firms over the five years. The variability for the non-failed firms was less than for the failed firms over the five year period.

EBIT/TA is identified in a number of prior studies as an important variable [e.g., Altman, 1968 and 1973, Altman and Lorris, 1976, Altman, et al.,1977 and Taffler

1977]. In essence, it is a measure of the true productivity of the firm's assets, abstracting from any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets. Furthermore, insolvency in a bankruptcy sense occurs when the total liabilities exceed a fair valuation of the firm's assets with value determined by the earning power of the assets. A firm with a poor profitability and financial problems is expected to go bankrupt. In this study, all of these ratios remained remarkably stable for the non-failed firms and rapidly declined for the failed firms over at least three year prior to failure. The ratios of the failed groups deteriorate as the years of failure approaches.

2. Capital Turnover Ratios:

The means of the capital turnover ratios for failed and non-failed firms do not appear either to be stable or significantly different, until 2 years prior to failure. The means of non-failed firms are not always stable five years prior to failure but WC/TA showed a relatively stable trend over the five years. The means for non-failed firms were above those of failed firms five years prior to failure. Four ratios in this financial structure have clear differences: QA/TA, FF/TS, NW/TS, WC/TA, are in the expected direction. Among them 7 capital turnover ratios, the FF/TS and WC/TA are the appealing ones, in the first year prior to failure, although WC/TA is greatly different, as failed firms lack sufficient working capital.

3. Financial Leverage:

The means of the TL/TA and TL/NW ratios for failed and non-failed firms do not appear either to be significantly different from each other until two years prior to failure. The means of failed firms were above those of non-failed firms for five years prior to failure. Whilst the means of the above both ratios for non-failed firms remained around the value of 50 and 120 the corresponding ratios for failed firms varied substantially within the range of +60 to +74 and +170 to +300. LTD/CA ratio shows that the expected direction between failed and non-failed firms for five years prior to failure. The differences between the means (C.G) of failed and non-failed firms were marked for five years BF failure where failed firms had obviously higher mean than non-failed firms. The means of the FF/CL and RE/TA ratios for failed firms were below those of non-failed firms five and four years prior to failure and showed a slightly dramatic fall three years prior to failure.

4. Liquidity Ratio:

The short-term liquidity of an enterprise is measured by the degree to which it can meet its short-term obligations. Liquidity is a matter of degree. A lack of liquidity may mean that the enterprise is unable to take into account favourable discounts or take advantage of profitable business opportunities as they arise. A profile of the short-term liquidity ratios mean values of the TD/TC, TD/TA, CA/CL, QA/CL, and CL/NW, and CL/TA for non-failed firms remained relatively stable over the five years. The mean value of the current ratios for the non-failed firms remained between 1.8 and 1.9 over the five years. The mean value of the current ratio for the failed firms varied somewhat between 1.5 and 1.2 five years prior to failure. The general profile for the CA/CL, QA/CL, CL/TA, and QA/TL over the five years are similar. The CL/NW ratio for failed firms were slightly below non-failed firms five year prior to failure, similar for four to two years prior to failure, and showed a dramatic rise above the non-failed firms one year prior to failure.

5. Cash Position

Too high a rate of turnover in TC/TS may be due to a cash shortage that can ultimately result in a liquidation crisis if the enterprise has no other ready sources of funds available to it. Too low a rate of turnover may be due to the holding of idle and unnecessary cash balances. TC/CL measures how much cash is available to pay current obligations. No cash to pay coming debts or to operate the company will force the firm into bankruptcy. A profile of the cash position ratios TC/TS and TC/TA illustrates relatively large differences for the failed and non-failed firms prior to failure. The difference between TC/TA and TC/CL is more significant compared with TC/TS.

6. Inventory Turnover

The means of the inventory turnover ratios CA/TS and TS/WC for failed and non-failed firms do not appear to be significantly different from each other at all. TS/WC ratio is a measure of the sales relative to the net liquid assets of the company. Working capital is the surplus of current assets which can be realised in the short run, over and above those needed to meet short-term claims on the company. This ratio (TS/WC) was found to be the best indicator differentiating between failed and non-failed firms by Deakin [1972], Edmister [1972] and Chen and Shimerda [1981]. However, the trouble with the liquidity ratios is that they ignore the dynamic nature of business. Companies are constantly paying off existing current liabilities and incurring new ones, and also constantly realising current assets and generating new ones by way of fresh sales. So the total current assets never become realised and the total current liabilities are never fully paid off. Further, there is also the problem of "window dressing" whereby companies may try to improve their current ratio by collecting debts just before the date of the balance sheet. There are also problems relating to the valuation of stocks. Forced sale value may be less than cost, which is the figures at which stock is usually valued; whereas normal sales value may be significantly greater. Therfore, any comparison of the totals of current assets and current liabilities is not a particularly helpful measure of the ability of the company to meet its current obligation as and when they fall due. The trend direction of the INV/TS ratio for failed and non-failed firms are the same five years prior to failure. The means of CA/TS and INV/TS failed firms were above those of non-failed firms for five years. The mean of TS/WC for the failed was above that of the non-failed firms, but showed a dramatic fall down two years prior to failure.

7. Receivable Turnover

The means of the receivable turnover ratios QA/INV and QA/TA for failed and non-failed firms appear both to be significantly different from each other. The trend direction for these two ratios for failed and non-failed firms are the same five years prior to failure. Based on the PEMC [1975] and PMC [1973] results and supplemented with the analysis of the data, the ratio, receivables/inventory, loads heavily on the receivables turnover factor in their study. Because of this relationship, the ratio quick assets/inventory is classified as belonging to the receivables turnover factor [see Chen and Shimerda, 1981].

8. Other Ratios

The profiles of the OP/TP and Interest Coverage ratios show that the differences between the mean values of the two groups did not appear to be as high as would be needed to aid the effective separation of failed and non-failed firms. The IC/TS ratio for failed firms tend to hold a higher level of interest charge to total sales than non-failed firms. Log[TA] have been trending upwards but dramatic down turn for the failed firms in the first year prior to failure

FIGURE 8-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES

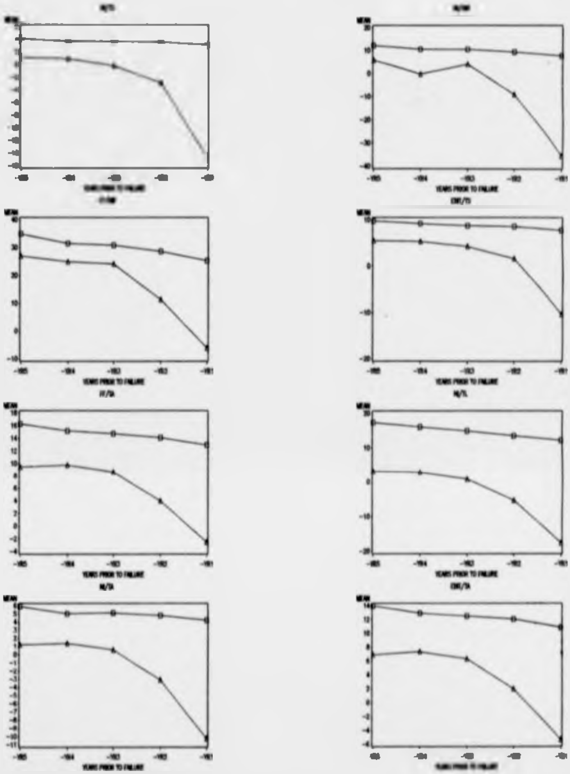


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FIGURE 8-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES

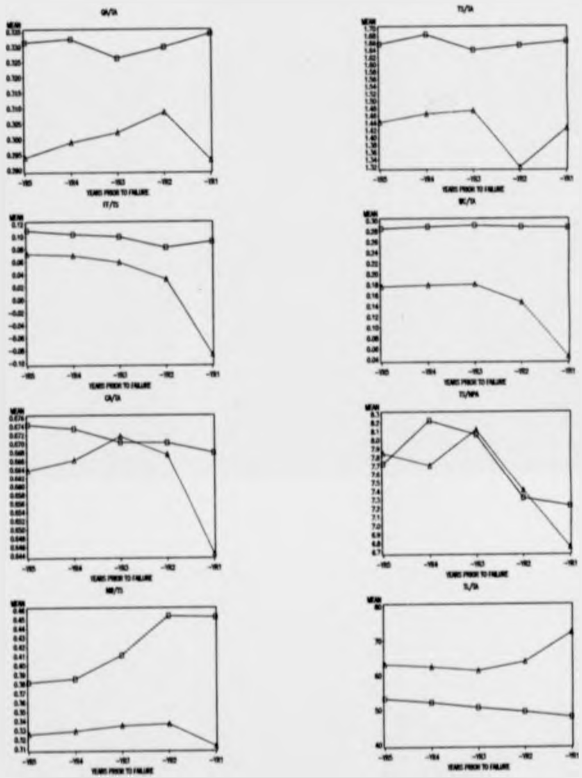

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FIGURE 6-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES

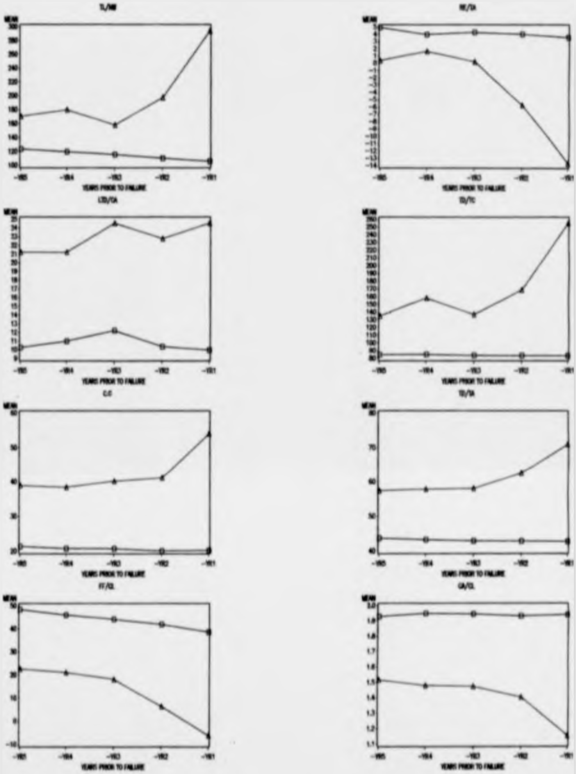

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FIGURE 6-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES

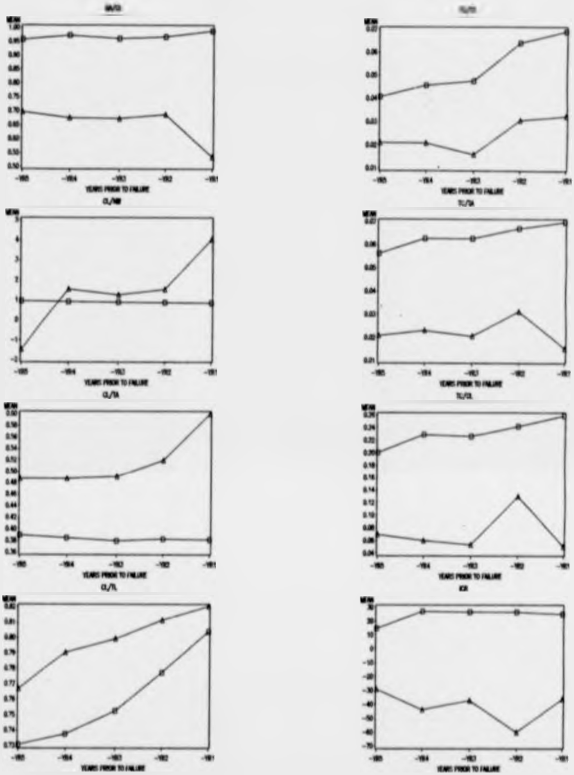

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FIGURE 6-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES

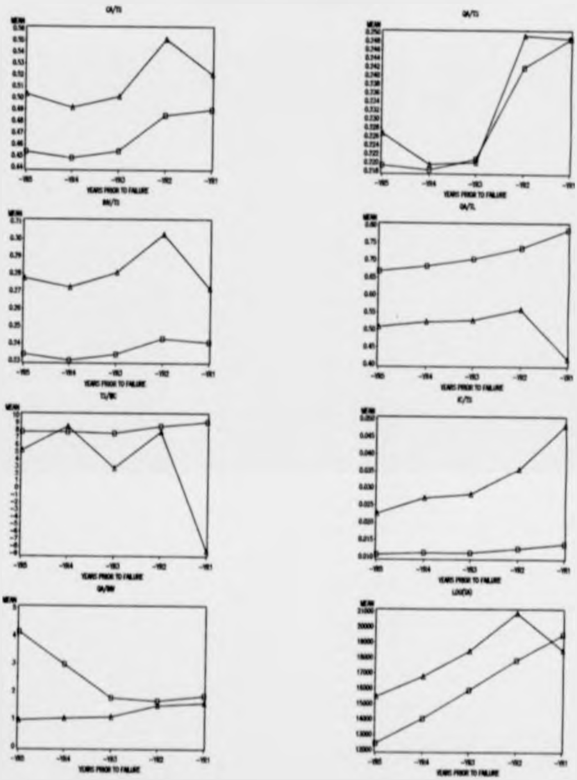

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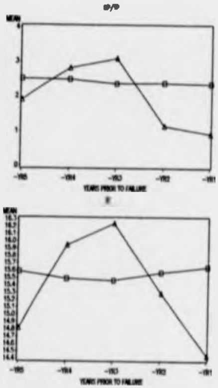
FIGURE 6-1
UNIVARIATE (PROFILE) ANALYSIS
COMPARISON OF MEAN VALUES



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6.5 The Industry and Economic Environmental Effects

6.5.1 Cluster Analysis

Cluster analysis is a technique for grouping individuals or objects for which the number and characteristics of the groups are to be derived from the data and are not usually known prior to the analysis. Grouping includes a collection of techniques that are used to group multidimensional entities according to various criteria based on their degrees of homogeneity and heterogeneity. As described above (see Section 4-2.3), one group of authors has ignored existing Standard Industry Classification (SIC) and has used statistical cluster analysis based on observable and measurable financial performance criteria. Another group of authors has taken existing SIC code and has measured the homogeneity of companies within industrial groups compared to the heterogeneity of companies in different groups.

Closer examination of the problem, however, reveals that there is a common core to all these studies. Those authors testing for homogeneity within and heterogeneity between standard groups used financial ratios as the criteria to measure company and industry performance. Those authors who relinquish existing groupings and attempt to design their own also use financial ratios as the criteria for determining which companies are most similar to one another. If financial ratios are to be used as the principal means of analysing company performance, then it is valid to examine inter- and intra-industry differences using ratios. It would be wrong, however, to use ratios as a means of grouping companies, and then to claim that the clusters thus produced were better than SIC schemes; they may be better for some applications, but are by no means universal. The cluster analysis study by Gupta and Huefner [1972] demonstrates the instability of clusters when the criterion variables are changed.

There is overwhelming evidence from those and other studies that companies can be aggregated into groups according to their financial ratio characteristics, and that these groups are very different from one another. For this reason, it is necessary to make adjustments to take these differences into account. Unfortunately, a fundamental difficulty arises when one attempts to find an objective criterion for grouping companies. Many cluster analysis studies to date have used a particular variable to cluster companies, and have then gone on to show that these clusters are better at predicting' this variable than other grouping schemes. This would appear to be a tautologous use of the technique [Galitz, 1985].

Cluster analysis was considered for use in this study, but was rejected. To allow companies to group themselves freely, based on Stock Exchange Standard Industrial Classification Scheme, was considered. This was contrived by actuaries to group firms facing similar exposures to political and economic influences, and therefore has a sound and relevant basis for this study. Although this scheme is not perfect, as Sudarsanam and Taffler [1985] show, it appears to be no worse than other techniques, including cluster analysis.

For the development of industry-specific models, the total 16 heterogeneous industries in this study are re-classified into five broad homogeneous groupings (1) Contracting, (2) Engineering-General, (3) Textile, (4) Other manufacturing, and (5) Miscellaneous industry on the basis of Stock Exchange SIC Scheme (see Table 6-15). Each industry is included in one of these five groups of broad classification. Since our five groupings are different from each other they may be used to represent five specific industries(see Table 6-10 below)

6.5.2 The Industry Factor

6.5.2.1 Industry Relative Ratios

Industry Relative ratios in each of the 16 sectors were derived from the weighted average ratios of the firms reporting to DATASTREAM. Industry relative ratios are calculated as demonstrated above (see section 4-5). Producing the industry relative ratios [IRR] is repeated for each of the failed and non-failed firms including year from 1971 to 1985, a total 15 year time span. For example, firms failed at 1975, we selected IRR ratios starting year from 1975 prior to failure for five years to calculate the industry relative ratio, firms failed at 1985, the time period will cover from 1981-1985, and so on.

Table 6-10 Standard Industrial Classification - For 16 industries

Industrial Groups	Industrial Group Number	Industrial Group Code	Industry Group Name
Contracting Groups	2.	BLDNG	Building Materials
	3.	CONTR	Contracting
Engineering-General Groups	4.	ELTCA	Electricals
	7.	ENGEN	Engineering
Other Manufacturing Groups	8.	METFM	Metal Forming
	9.	MOTGP	Motors
	22	BRDIS	Brewers & Distillers
	25	FDMFG	Food Manufacturing
	31.	PKPAP	Packaging & Paper
	42.	CHMCL	Chemicals
Textile Groups	35.	TEXTL	Textiles
Miscellaneous Groups	32	MEDI	Media
	34	STORE	Stores
	43.	CONGL	Conglomerates
	44.	TRNSP	Transport
	48	MISCS	Miscellaneous

Note: See Appendix F for a more detailed classification.

One characteristic of the industry relative ratios is that this data transformation places all companies in rank order, regardless of industry, and on the same measure. Using the industry relative ratios may change one's recognition of the profitability of a company. An example in Table 6-11 includes normal and industry relative (mean) , NI/TS, ratios for five failed and non-failed firms obtained from this study. Each company came from a different industry. The first set of columns labelled "Normal Ratios" lists the NI/TS ratios for each of the five firms in the two groups. Assuming that the higher the NI/TS ratio, the better off the firms, in the failed group, Cope Sportwear, would be evaluated the best of the group, while Cocksedge Hdgs would be considered the second best firm, Barget would be viewed as the worst. In the non-failed group, Metalrax, would be assessed as the best, Ward Holding as the second, Shiloh Group would be estimated as the worst. On the contrary, a different inference would be reached if one considered the industry relative ratio (NI/TS) shown in the second set of columns in Table 6-11, because each failed and non-failed firms comes from a different industry having a different capital structure, as reflected by the industry relative (NI/TS) ratio, a very different rank ordering of the firms is obtained. (From this view point, industry relative ratios are generally influenced by the financial structure at different level unless the structure of each firm at the homogeneous sector is taken into account). Furthermore, as shown in Table 6-11, by placing all firms, regardless of industry, on the same scale, the industry relative ratio imposes a metric with meaningful intervals on the data. That is, (1) A company that has an industry relative ratio of 0.011 indicates that the company's ratio is ten percent higher than the industry relative ratios of 0.01. The same conclusion is not evident using unadjusted ratios, since it is difficult to assess the relative position of companies across industries [Platt & Platt, 1990].

Table 6-11 Industry Relative Ratios of Failed and Non-Failed Firms Across Industries in This Study

UNADJUSTED RATIOS					INDUSTRY RELATIVE RATIOS		
Firms	Failure Year	Datastream Code	NI/TS Ratio (1)	Rank Order	Industry Average (2)	Industry Relative Order (3)	Rank Order
Failed Firms:							
Cocksedge Hdgs	1984	CONTRA	-3.69	2	2.24	-1.64	3
Acrow P.I.C	1983	ENGENA	-6.60	4	2.01 -	3.28	4
Caravans Int.	1981	MOTGPA	-4.20	3	-0.07	60.00	1
Cope Sport	1979	TEXTLA	-3.32	1	3.51 -	0.94	2
Barget	1983	MISCSA	-53.84	5	3.16	-17.03	5
Non-failed Firms							
Ward Hold.	1980	CONTRA	5.67	2	2.05	2.76	1
Metalrax	1978	ENGENA	6.09	1	3.41	1.78	2
Plaxton	1981	MOTGPA	3.64	3	-0.07	-52.0	5
Shiloh	1980	TEXTLA	0.59	5	2.36	0.25	4
CRT Group	1980	MISCSA	1.66	4	2.92	0.56	3

Note: Industry Average (2) = Industry Mean Ratio (see Appendix E).
Industry Relative Ratio (3) = Ratio (1) / Industry Average (2)

6.5.2.2 Industry Effect

Nearly all of the previous studies have attempted to adjust for the industry effect by stratifying the samples on the basis of similar industry classification. Gonedes [1969], Martin [1971] and EL Hennawy and Morris [1983] used dummy variables to cope with the industry effect. In this study, as described above (see chapter 4-2), the use of traditional raw ratio can lead to significant industry sensitivity. A method that would adjust the raw ratios to reduce the impact of industry differences is industry relative ratios. However, Izan [1984] and Platt and Platt [1990] successfully employed industry relative ratios either in linear discriminant functions or in logistic regression functions. 16 industry relative ratios, 41 financial ratios, four macro-economic variables, and 11 year dummies are used in this study and are empirically examined for five industry specific discriminant functions.

6.5.3 The Business Cycles and Year Dummy Variables

The bankrupt companies in the sample used in this study failed in the period from 1974 to 1985. The following set of 11 year dummy variables are developed to represent each year of the 11 years factor indicators (see Table 6-12).

Table 6-12 Eleven Year Dummy Variables Used From 1974 to 1985

	Yr1	Yr2	Yr3	Yr4	Yr5	Yr6	Yr7	Yr8	Yr9	Yr10	Yr11
1974	1	0	0	0	0	0	0	0	0	0	0
1975	0	1	0	0	0	0	0	0	0	0	0
1976	0	0	1	0	0	0	0	0	0	0	0
1977	0	0	0	1	0	0	0	0	0	0	0
1978	0	0	0	0	1	0	0	0	0	0	0
1979	0	0	0	0	0	1	0	0	0	0	0
1980	0	0	0	0	0	0	1	0	0	0	0
1981	0	0	0	0	0	0	0	1	0	0	0
1982	0	0	0	0	0	0	0	0	1	0	0
1983	0	0	0	0	0	0	0	0	0	1	0
1984	0	0	0	0	0	0	0	0	0	0	1

The fact that observations are pooled in this study allow us to examine the differential impact of business cycles and time span on failure probabilities. Year dummy variables were examined here based on the year from 1974 to 1985. A regression on these year dummy variables was then carried out. Nevertheless, a three stage business cycle which divides all sample into expansion, recession and recovery, (three homogeneous economic conditions) is also examined (see Table 6-13).

In Table 6-13, We have provided a summary of the interest rate, annual inflation, and Real GNP in this period. Interest rate, inflation rate, and real GNP are as discussed previously in Chapter 4. The interest rates shown are the UK three month treasury bill rate. The inflation rate is the percentage rate of increase of the level of prices during a given period. The rate of inflation shown in Table 6-13 fluctuates moderately. The inflation rate presented is the UK retail prices index - All items - Annual inflation rate. The real GNP measures the output produced in any one period at the prices of some base year. Real GNP, which values the output produced in different years at the same prices, implies an estimate of the real or physical change in production or output between any specific years. The growth rate of the economy is the rate at which real GNP is increasing. The business cycle is the more or less regular pattern of expansion (recovery) and contracting (recession) in economic activity around the path of trend growth. The trend path of GNP is the path GNP would take if factors of production were fully employed. The real GNP displayed is the Gross National Product at 1985 market Prices. An examination of Table 6-13 displays that the sample period can be divided into three subperiods based on the degree of movement of the three macro-economic variables. The purpose of this study is to analyse the relationship between business cycles and business failure.

1. Period 1: steady growth phase. In this study, this period covers Jan 1974 to April 1979 and was marked by moderately stable growth in GNP and diminishing annual inflation rate and UK treasury bill rate. Table 6-13 shows that there is the period of steady inflation and interest from 1975 to 1978. Companies failing in this period were expected to reflect the conditions expected in the expansionary period with both inflation and interest rate effects dominant (see: Table 6-13). **Period 1 is structurally similar to period 3, so both periods can be characterized as recovery**

2. Period 2 : Recessionary Phase. In this study, this period covers May 1979 to May 1981 and was marked by a slow-down in real GNP. The inflation and treasury bill rate rose strongly in the beginning and began to decline by the end of the period. Companies failing in this period were expected to present the conditions expected in

the recessionary phase, combined with the effects of high inflation and interest rates. Exports fell in 1979-1981, partly because of the world-wide depression and partly because the exchange rate was allowed to rise. In the recession there is sizable decline in fixed investment, which by 1981 was running at its lowest level.

3. Period 3: Steady growth phase. In this study, this period covers June 1981 to Dec 1985 and was marked by steadily increasing GNP and moderate movements in inflation and interest rates. Companies failing in this period were expected to display the characteristics described for the recovery phase. The slow-down of inflation rate and increasing of GNP suggest that the factors identified for those conditions should have had minimal impact in this period.

6.5.4 Macro-Economic Variables

Several authors (Dambolena and Khoury, 1980, and Rose, Andrew and Giroux, 1982) have suggested incorporating a macro-economic variable in prediction of failure research. In this study, industry-specific models incorporate four macro-economic variables for each year. The macro and economy-wide variables can be represented by a large number of variables which purport to reflect the general state of the economy. Four macro-economic indicators, interest rate, annual inflation rate, real GNP, and industrial production, are used to develop an economy-wide indicator. The definition of the variables is defined as above previously. Four variables are derived from international UK Datastream. These variables is used to develop specific industries failure prediction models, and to test if the macro-economic variables can classify failed and non-failed firms prior to failure [see chapter 9]. Each indicator could be used in different forms to measure different aspects of the state of the economy. Inclusion of the macro-economic variables in the industry-specific models may make the model more reflective of prevailing economic conditions in a one industry-specific as compared to the aggregate and other industry-specific models.

Table 6-13 Levels of Interest Rates, Annual Inflation Rate, and Real GNP in Period of Failure For Sample

Year	Quarter	Interest Rate	Annual Inflation Rate	GNP At 1985 Market Prices	Homogeneous Period
1975	1	9.41	20.30	83.7	
	2	9.56	24.27	82.5	
	3	10.56	26.57	82.2	
	4	10.58	25.31	83.0	
1976	1	8.38	22.47	84.7	
	2	10.97	16.03	84.2	
	3	12.88	13.65	84.8	**Period 1**
	4	14.47	14.93	86.7	(Jan 1975 - Apr 1979)
1977	1	8.88	16.51	86.7	
	2	7.47	17.41	86.4	
	3	5.25	16.58	87.0	
	4	6.22	13.08	88.4	
1978	1	6.00	9.50	88.9	
	2	9.33	7.68	90.0	
	3	9.19	7.85	90.8	
	4	11.64	8.09	91.3	
1979	1	11.38	9.58	90.7	
	2	13.38	10.58	94.7	
	3	13.21	15.98	92.5	
	4	15.88	17.26	93.3	
1980	1	16.27	19.08	92.8	**Period 2**
	2	15.67	21.55	91.0	(May 1979 - Jun 1981)
	3	14.36	16.36	90.3	
	4	13.05	15.28	89.3	
1981	1	11.61	12.71	89.0	
	2	11.91	11.70	89.1	
	3	15.72	11.26	90.2	
	4	14.80	11.91	90.3	
1982	1	12.59	11.13	90.3	
	2	12.34	9.35	91.2	
	3	9.77	7.98	91.3	
	4	9.75	6.17	91.9	
1983	1	10.28	4.97	93.5	
	2	9.34	3.78	94.1	
	3	9.00	4.64	94.7	**Period 3**
	4	8.84	5.05	95.7	(Jul 1981 - Dec 1985)
1984	1	8.47	5.16	96.5	
	2	8.81	5.14	96.2	
	3	10.06	4.71	96.2	
	4	9.13	4.84	97.3	
1985	1	13.31	5.52	98.9	
	2	11.95	6.96	100.2	
	3	11.06	6.32	100.3	
	4	11.14	5.52	100.7	

Source: International Datastream Inc.(1975-1985)

6.6 Summary and Conclusions

This chapter has shown the results of statistical analysis on the independent variables. The distributional properties and outliers of financial ratios, correlation analysis, univariate analysis, T-test, industry relative ratios, year-dummies, macro or economy-wide indicators were discussed.

Financial ratios included discriminating a priori grouping of the initial two groups and detecting the overlapping problems between or among ratios. Outliers always exist in financial ratios, and it is more difficult to make financial ratios approach normality if outliers are included. Hence, a number of possible transformations are applied to ensure that the ratios distribution of approach normality. The results of this section show that only the distribution of WC/TA and TL/TA are appear to approach normal without transformation. Of the 42 financial ratios initially considered in this study, R32 (defined as above) is excluded because of missing values. The distribution of each of the 41 financial ratios, the treatment of outliers, data transformations and descriptive statistics are all presented in this chapter. Comparison between the means of failed and non-failed firms via univariate analysis indicate there is a clear difference for at least as far back as three years prior to failure.

The highest correlation between two ratios is R1 NI/TS and EBIT/TS, the second highest is between FF/TA and EBIT/TA. Correlation analysis can indicate the relationship between two ratios and show the collinearity problems. For the 41 ratios, collinearity can not be avoided. As already described above, the inclusion of collinear financial ratios in statistical models produces the multicollinearity problem, it is more difficult to interpret the models due to inconsistent parameters.

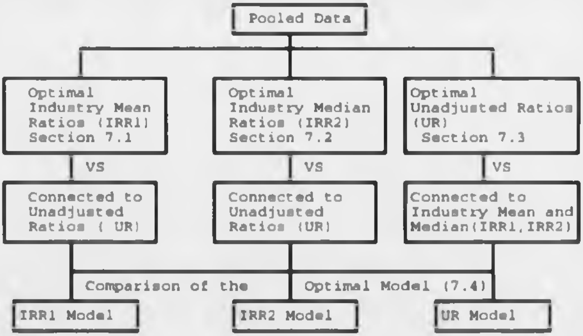
As for the industry effect, we used paired samples based on similar total assets, corresponding year and same industry for failed and non-failed groups as criterion to control the industry effect. For each of the 16 sectors 41 accounting ratios are calculated from the Datastream computer program to bring about the industry relative ratios in order to cope with the problem of data instability over time and across industries. Instability of financial data over time is not a new idea.

To remedy the problem of data instability, Dambolena and Khoury [1980], and more recently Betts and Belhoul [1987] used the variation in financial ratios to measure the stability of the ratios. We did not do so in this study. We hope to explore a more promising method to effectively deal with data instability is to create industry relative variables by relating the same ratio for a firm to that for the average firm in its industry. Another is to forecast business cycle models, and to estimate industry-specific models. The empirical result using industry relative ratios will be displayed in Chapter 7. We used macro or economy-wide indicators (interest rate, annual inflation, and real GNP, see Table 6-13) to classify the different periods of time into different phases of the basic business cycles. The three different time periods derived indicate the differences among three phases of a business cycle (recessionary, expansionary and recovery periods). Business cycle models will be presented in chapter 8. Additionally five industry-specific models will be examined in chapter 9.

Chapter 7 Empirical Results : Industry Relative Ratios

Lev [1971] found that financial statement variables are unstable over time, especially those representing failing firms. Instability may arise for different economic and political reasons. Barnes [1990] reported the reasons as: inflationary effects, technological change and changing accounting policies. However, it is possible to "**stabilize**" accounting data. For example, Dambolena and Khoury [1980] and Betts and Belhoul [1987] used the coefficient of variation of the ratios as a measure of their stability. Mensah [1984] considered the business cycle problem. Izan [1984] and Platt and Platt [1990] used industry relative ratios to cope with this instability problem. In this study, firstly, we develop different failure prediction models on the basis of our different research hypotheses discussed earlier (see: hypotheses, H_1 to H_3). Secondly, we test the three different phases of business cycle (see hypotheses, H_4 to H_{18}). Finally, each specific industry results will be presented (see hypotheses, H_{19} to H_{24}). The testing involved is moderately complex and a flowchart of chapter 7 is presented in Table 7-1. The broad strategy is to develop an optimal model for one ratio form (UR, IRR1, IRR2) and then compare it to its connected model using the same coefficients but converting the ratio form to its alternative types (IRR1 to UR, IRR2 to UR, UR to IRR1, UR to IRR2).

Table 7-1 Flowchart of Chapter 7



7.1 Empirical Results for Industry Relative Ratio (IRR) Model

The purpose of this chapter is to derive a discriminant function [see chapter 5.4.1] and test the out of sample forecasting stability of a business failure model using industry relative (mean and median) ratios. Platt and Platt [1990] have identified "the big problem is out-of-sample (ex-ante) classification results that are ten or more percentage points lower than the model's within-sample (ex-post) results". The instability between ex post and ex ante sample performance is a most pressing issue in the field of failure prediction. To investigate this problem, the results derived from the discriminant function for the ex post sample are used to classify the ex ante sample cases. The results are set out in 7.1.2 to 7.4 sections. We start with a description of the methods used in selecting the independent variables that enter the discriminant function will be made.

Variable selection in the SAS STEPDISC procedure was used for data reduction. Variables are selected to enter the model according to the following two criterion:

1. A significant level of an F test from the analysis of covariance. In this test the variables already selected act as covariances and the variable under consideration is the dependent variable.
2. High partial correlation between the variable under consideration and dependent variable, controlling for the effects of the variables already selected for the model.

In this study, the significance of the variable entering or remaining in the model is assessed by the multivariate partial F-test. This is a measure of the discrimination introduced by the variable given the other variables already in the model [see Eisenbeis and Avery, 1972]. Financial ratios were selected on the basis of their discriminating power or the particular selection criterion used.

A failure prediction model was developed for each of the three years prior to failure respectively. We considered whether to develop discriminant functions for each calender year 1974, 1975, 1976 and so on up to 1985 (11 years in all) or to pool the data for separate years. Since the annual calender time function requires a much larger data set than pooling data, inevitably we pooled. Thus one year prior to failure includes data on companies that may have failed at any time between 1974 and 1985, the financial data used being between 1973/1974 and 1984/1985. The aims of developing all these models were (1) the conventional one, to consider how the early warnings of failure are reflected in the accounting ratios, (2) the exploratory one, to test whether ex ante sample predictive ability can be improved prior to failure using industry relative (mean and median) ratios.

In the following sections, we will discuss the empirical results using industry mean ratios (IRR1), industry median ratios (IRR2) and unadjusted ratios (UR). Each of the models reported below are developed over a ex-post time period prior to failure and their functions are used to forecast over the ex-ante time period. The investigation is to see how much their performance is improved compared with unadjusted ratios and previous studies.

In order to compare our results with that of Platt and Platt's [1990] model and with that of Izan's [1984] model, the models are first developed with costs of misclassification assumed equal, and prior probabilities of failed and non-failed firms assumed to be 1:2 in accordance with the sample proportions. Subsequently the sensitivity of these comparisons to incorporating realistic prior probability and misclassification costs are discussed.

7.1.2 The Model: Using Industry Mean Ratios (IRR1).

The two basic assumptions of Linear Discriminant Analysis (LDA) are (1) the independent variables of each group are multivariate normally distributed; and (2) the group dispersion (variance-covariance) matrices are equal across all groups. However, Hennawy and Morris in 1983 stated that a linear discriminant function performs fairly well even when discrete data, (such as dummy variables, or small samples) is included. Lanchenbruch [1975] confirmed that the linear discriminant function is not especially sensitive to minor violations of the normal distribution assumption. Sudarsanam and Taffler [1985] also proved that a quadratic function may indeed perform worse than a linear function when there are small samples relative to the number of discriminant variables and when the groups are not widely separated. Given these points, it was decided to use the linear discriminant function rather than the quadratic form in this study.

The ex post sample of 52 failed firms and 104 non-failed firms (see section 5.2.4) were used to develop each failure prediction model. The predictive ability of the model was tested against the ex ante sample of 108 companies, of which were 36 failed and 72 non-failed. As shown below, this industry mean model provides one year early warning and its ability to discriminate increases as firms approach failure. The discriminant equation is a linear form:

$$Z_i = b_0 + b_1 X_{1i} + b_2 X_{2i} \ldots\ldots + b_n X_{ni}$$

Where :

$b_1, b_2 \ldots\ b_n$ = Discriminant Coefficients

$X_{1i}, X_{2i}, \ldots X_{ni}$ = Independent Variables

Where Z_i take a value of one for a failed firm and zero for a non-failed firm. The coefficients and other statistics of IRR1 model are shown as follows:

$$Z_{IRR1} = -5.77 + 5.20(FF/CL) - 4.46(IC/TS) - 2.16(NI/NW) - 0.86(OP/TP) + 1.08(TS/NPA)$$

Where:

FF/CL (Funds Flow / Current Liabilities). This measures how many times current liabilities are covered by the funds flow of the year just elapsed. It is, of course, backward looking while current liabilities of a certain date must be paid out of future, rather than past, funds flow. As might be expected, an extremely low funds flow relative to short-term commitments is a predictor of failure [Edmister, 1972]. This ratio was one of the most significant variables of Edmister's.

IC/TS (Interest Charge / Total Sales). In a period of high interest rates or credit unavailability, failure may be induced by rising borrowing costs in excess of sales profit margins. This ratio can also be seen simply as a scale adjustment.

NI/NW (Net Income / Net Worth). Net income and earnings are synonymous with profit. Net income is defined as a net flow (inflows minus outflows) of assets to the firm from all sources other than owners and any donations received. Net worth is also known as equity. This ratio measures the rate of return on stockholder investment or return on equity and gauges its progress. Fitzpatrick [1932] and Elam [1972] found this to be the best predictor of their studies. The sign of the coefficient is negative which appears to be anomalous. The coding of Z_i as one for a failed firm means that higher values of return on equity, reduce the Z-score and the probability of classifying a firm as failing.

OP/TP (Operating Profit / After Tax Profit). Operating profit is net profit derived from the normal activities of the company after depreciation. This item is adjusted to reflect any items of an exceptional nature. After tax profit shows profit, adjusted for items which do not relate to the normal trading activities of the company, net of tax. Operating income arises from the firm's production and exchange transactions. The income elements indicate different aspects of managerial performance. Again the sign of the coefficient is not as would be anticipated in a univariate study. The behaviour of partial coefficients when the ratios are selected to summarise a wide variety variables is complex. The power of the model is best understood as deriving from the whole set of variables.

TS/NPA (Sales / Net Plant Assets). While the relationship between property, plant, and equipment and sales is a stable one on a long-term basis, there are many short-term and temporary factors which may upset this relationship. Among these factors are conditions of excess capacity, inefficient or obsolete plant, multi-shift operations, temporary changes in demand, and interruptions in the supply of raw materials and parts. Increases in plant capacity are not gradual but occur, instead, in lumps. This too can create temporary and medium-term changes in the turnover rates. Often, leased facilities and plants, which do not appear on the balance sheet, will distort the relationship between sales and net plant assets. The ratio in a univariate sense measures capital intensity with low values corresponding with more asset intensive businesses.

The discriminant function is helpful in indicating the direction and degree to which each variable contributes to the classification. If the sign of a variable's coefficient in the model is positive then large values of the ratio imply a larger Z-score, and a greater chance of belonging to the failed group. The converse applies if the coefficient is negative.

There are different 60 models repeated in this study, so clearly a detailed review of coefficients and ratios must remain a task for the reader. We have set out an illustrative review for the first models, however a word of caution is that in a multivariate setting each ratio may be repeating or "standing-in" for a number of closely correlated ratios.

Only if the ratios are orthogonal are the coefficients independently interpretable. This is the essence of the multi-collinearity problem in multi-variate analysis. If it is positive, the individual with larger values of the corresponding variable tend to belong to failed company, and vice versa. The positive coefficients of the above model's accounting ratios indicate that the two ratios act in the same direction so that the higher the value of each of them the more solvent is the company. The within groups correlation matrix which is shown in Table 7-2. This Table shows that the highest correlation coefficients is (-0.34). As stated in Chapter 5, it was found that any negative correlation among the independent variables increases their discriminating power.

7.1.3. Model Significance Test

SAS provides the multivariate Statistic and exact F statistics to examine the contribution of classification variables in this model. The null hypothesis being tested is that none of the variables improves the classification based on chance alone. Equivalent null hypotheses are that the two population means for each variable are identical, or that the population D^2 is zero. The validity of the model was in fact strongly confirmed by the F statistics at the relevant degrees of freedom, all of which were highly significant at the 0.001 level. The test statistic in this study for the calculated F value (6, 149) = 50.08, Mahalanobis D^2 is 7.41. These five variables together provide an impressive degree of classification accuracy. The significance levels of all independent variables are highly significant at the 0.001 level.

7.1.4 Relative Contributions of Ratios

Table 7-3 displays the relative contribution of the independent variables based on the standardized discriminant coefficients and Mostellers' and Wallace's methods. It is seen that FF/CL has a remarkably large effect on the discriminant function between failed firms and non-failed firms. However, the relative contribution of the each variables, in general, to the discriminant function is not consistent.

7.1.5 Examining the Classification Accuracy - Using Industry Mean Ratios (IRR1)

In this chapter, we use the discriminant function developed from the ex post sample and apply it to the ex ante sample to examine predictive ability comparing classification results from ex post (within-sample) to ex ante (out-of-sample) periods. The hypothesis being tested investigate whether using industry mean ratios solve the data instability problems endemic to bankruptcy prediction.

7.1.6 Ex Post and Ex Ante Sample Test

The classification accuracy for the ex post sample analysis using industry mean ratios is given in Table 7-4. The results are indeed impressive and comparable to previous successful studies. The ex post sample resulted in 4 non-failed firms being misclassified from 104 non-failed firms and 8 failed firms being misclassified from 52 failed firms. The Type I accuracy is 84.6% (44 of 52 correctly classified) and the Type II accuracy is 96.1% (100 of 104). Overall, the accuracy is 93% (144 of 156).

The classificatory power of the IRR1 model is statistically significant compared to the proportional chance model. In this section, for example, given $q_1 = 0.33$, $q_2 = 0.67$ and cost ratios = 1 (see: chapter 5.8), the percentage of correct classification from the chance model is 55% (which is the sum of $(0.33)^2 + (0.66)^2$). The percentage of correct classification from the IRR1 model is 93% (which is the sum of 0.67(100/104)

+ 0.33(44/52)). The test statistic (see subsection 5-8, equation 5-12) for the difference between the results and proportional chance is 9.74. This has a normal distribution, with 0.001 significance level.

Validation results examine the ability of the model to predict failure or non-failure among a new set of companies. Validation tests in prior literature have employed a variety of methods, including a jackknife method, or Lachenbruch [1967] test; a hold-out sample test using a new sample within the sample time period; or a forecast test using a sample of new companies from a later time period. In this study, two validation tests[1], a Lachenbruch U-method (Lachenbruch and Mickey, 1968) which classifies each observation using a MDA model estimated from all other observations, and a forecast test, were used.

The result for the Lachenbruch cross-validation bias test is exactly identical to the original sample (93% vs 93%), indicating that the results are not sensitive to sample bias. Table 7-6 reports these results. The second validation was a forecast test in the model was used to classify a new sample. Data for thirty-six failed companies and seventy-two non-failed companies during the period 1982 to 1985 was included. Table 7-5 shows this test resulted in 4 non-failed firms being misclassified and 4 failed firms being also misclassified. Type I errors is 11.1% (4 of 36) and that for the type II errors is 5.5% (4 of 72) in the forecast test. Overall, the misclassification rate is 7.4 per cent. The overall accuracy for both within-sample (ex-post) and out-of-sample (ex-ante) are identical (93% vs 93%). These results indicate that the industry relative adjustment does give indeed a stable classification model one year prior to failure, confirming the results reported in the literature by Platt and Platt [1990].

Table 7-2 Within groups Correlation Matrix - IRR1 Function

Ratios	IC/TS	NI/NW	OP/TP	TS/NPA
FF/CL	-0.17	0.28	-0.13	-0.34
IC/TS		-0.31	0.21	-0.10
NI/NW			-0.02	0.15
OP/TA				0.10

Table 7-3 Relative Contribution Tests of Each Independent Variables - IRR1 Model

Var.	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	1.71	1	44.48	1
IC/TS	-1.16	3	22.72	2
NI/NW	-1.27	2	17.55	3
OP/TP	-0.92	4	13.87	4
TS/NPA	0.72	5	1.36	5

The Value of the overall variables D^2 is 7.41

Table 7-4 Classifying the Within (Ex Post) Sample, Using IRR1 Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	100	4	104
Failed	8	44	52
Error Rates %	4%	15%	7%

Table 7-5 Predicting the Out-of-Sample (Ex Ante) - IRR1 Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	68	4	72
Failed	4	32	36
Error Estimate	6%	11%	7%

Table 7-6 Industry Mean Ratio Forecast Validation Results One Year Before Failure

Group	Percent Ex-post	Correctly Classified Lachenbruch	Ex-Ante
Non-failure	96%	96%	94%
Failure	85%	85%	89%
Overall	**93%**	**93%**	**93%**

7.1.7 Comparison With Models Using Unadjusted Ratios (UR)

Table 7-9 compares IRR1 classification results to those obtained with unadjusted ratios (UR). The model specification was not changed that is the same ratios were selected; therefore, the results are comparable [Platt and Platt, 1990]. 52 failed and 104 non-failed firms were examined, using the financial statement one year prior to bankruptcy. The accuracy of the models using UR data was compared to that of the IRR1 data which served as a criterion for evaluating accuracy. The model is statistically significant at the 0.001 level. Thus, the overall discriminating power of the UR function is highly significant. The Mahalanobis D^2 of unadjusted ratios is 7.72. The same five ratios as IRR1 model were used. The model's function fitted to the ex post sample as follows:

$$Z_{UR} = 5.58 + 0.78(FF/CL) - 1.80(IC/TS) - 1.45(NI/NW) - 1.15\,(OP/TP) + 0.84(TS/NPA).$$

Table 7-7 shows that within sample resulted in 5 non-failed firms being misclassified and 7 failed firms being also misclassified. The percentage of Type I errors made by the analysis model (i.e., non-failed firm misclassified as failed firm) is 4.8 per cent, and the type II error (failed firms misclassified as non-failed firms) is 13.4 per cent. The overall misclassification is 8 per cent. The result, therefore, is only 1 per cent less accurate than the ratios adjusted by the industry mean (see: Table 7-9).

Table 7-8 gives the forecast test results. The forecast validation resulted in 8.3% (6 of 72) non-failed firms being misclassified and 16.6% (6 of 36) failed firms being also misclassified. The overall misclassification rate is 11 per cent. The comparison of the forecasts using IRR1 compared to UR model both in ex post sample and ex ante sample are shown in Table 7-9. IRR1 shows a slight improvement over UR in the ex ante sample (93% vs 89%).

Table 7-7 Classifying the Within Analysis Sample, UR Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	99	5	104
Failed	7	45	52
Error Estimate	5%	13%	8%

Table 7-8 Predicting the Out-of-Sample, UR Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	66	6	72
Failed	6	30	36
Error Rate	8%	17%	11%

Table 7-9 Comparison of Error Rate Results: IRR1 and UR One Year BF.

	Error Misclassified Rate IRR1	UR	UR > IRR1 Difference
Within Sample:			
Non-failed	4%	5%	+ 1%
Failure	15%	13%	- 2%
Overall	**7%**	**8%**	**+ 1%**
Out-of-Sample			
Non-failed	6%	8%	+ 2%
Failure	11%	17%	+ 6%
Overall	**7%**	**11%**	**+ 4%**

IRR1 = Industry Mean Ratios, UR = Unadjusted Ratios

7.1.8 Comparison With Previous Studies

As described in above, failure models generally produce lower classification levels with ex ante sample data than with ex post data, as shown in Table 7-10 in order to provide a form of comparison with the present studies. Although, the prevailing economic condition during the relative period of these studies are not homogeneous, the results of the present study appear to be on comparable terms with the previous studies. Five financial ratios derived from IRR1 model one year before failure are different from Platt & Platt's [1990] model. The results of this study compared to Platt and Platt [1990] and other previous studies, are given in Table 7-10. In this study, overall and non-failed firms for both ex post sample and ex ante sample classification rates were more stable than those reported by Platt and Platt [1990]. The stability of the model ex ante sample classification rates when adjusted for industry mean compared with unadjusted ratios is consistent with the findings of Platt and Platt [1990]. The predictive ability of the model in the ex ante example using industry mean ratios in this study was found to be better than that of Platt and Platt's [1990] (93% vs 90%) and those of other previous studies respectively (See: Table 7-10).

Table 7-10 Classification Accuracy One Year Before Failure

			Percent Within-Sample (Ex Post Sample)		Correctly		Classified Out-of-Sample (Ex Ante Sample)		
Model	Statistical Method	Random/ Matched Sample	Failed	Non-Failed	All	Validation Test	Failed	Non-Failed	All
Altman,E.[1968],	MDA	M	94%	97%	95%	N2	96%	79%	84%
D Deakin, E., [1972],	MDA	R	97%	97%	97%	N1	82%	77%	79%
Altman, E. B Loris [1976]	MDA	R	90%	90%	90%	L	83%	88%	86%
Korobow,L Stuhr, P and Martin,D [1976]	Reg	NA	93%	87%	NA	N2	94%	75+	NA
Altman,E. Haldeman,R and Narayanan,P [1977]	MDA	M	96%	90%	93%	L	93%	90%	91%
Dambolena I & & S.Khoury [1980]	MDA	M	91%	100%	96%	L	NA	NA	87%+
Zmijewski [1984]	WESML,Prob								
	Even Weight	R	52%	100%	76%	H	54%	99.8%	76%
	20:1 Weight	R	42%	100%	97%	H	44%	100%	96%
Altman, E and H.Izan [1984]	MDA	M	94%	90%	92%	L	94%	90%	92%
Barth, Brumbaugh Sauerhaft, and Wang [1985]	Logit	NA	86%	87%	87%	N2	85%	78%	80%++
Frydman, Altman and Kao [1985]	RPA	R	84%	99%	94%	L	NA	NA	84%++
Pantalone and Platt [1987a]	MDA	M	93%	97%	95%	N2	86%	96%	95%
Pantalone and Platt [1987b]	Logit	M	93%	78%	83%	N2	82%	77%	79%
Betts and Belhoul [1987]	MDA	R	98%	92%	96%	L	82%	81%	81%+
Platt and Platt [1990]	Logit	M	93%	86%	90%	N2	91%	88%	90%
Present Study [1992]	**MDA**	**M**	**85%**	**96%**	**93%**	**N2**	**89%**	**94%**	**93%**

Reg: Regression, M: Matched, R : Random

H: Within sample period holdout test.

L: Within sample period Lachenbruch test.

N1: Out-of-sample period prior to estimation period test.

N2: out-of-sample period ex ante test.

+Difference between overall percentage correctly classified significant beyond the .10 level(one-tail)

++Difference between overall percentage correctly classified significant beyond the .025 level (one-tail)

Source: The Journal of Business Finance & Accounting [Platt & Platt, 1990] and This Study.

7.1.9 Sensitivity to Prior Probability and Misclassification Costs

In the above studies, I have assumed sample proportional prior probabilities and equal misclassification costs in order to compare our results with those of previous studies and that of Platt and Platt's [1990] model. Nevertheless, failure to consider prior probabilities is a valid criticism of earlier studies that assumed equal probability of group membership or probabilities based on sample proportions. The cost of misclassification errors should also normally be assessed in evaluating predictive success. For economically efficient decision making, however, the predictive functions should be customized to reflect the relative costs to the decision maker of the two types of misclassification. [see: Keasey and Watson, 1991]. In the following analysis, we employ more realistic prior probabilities and costs of errors instead of using sample proportion prior probabilities and equal costs in order to explore the sensitivity of the results.

We compare IRR1 and UR model efficiency under five various levels of input assumption. Prior probabilities of failed and non-failed were incorporated into the model by adjusting the constant term as suggested by Afifi and Clark [1984]. The above five variables were selected as independent variables in the model. Optimal cutoff points and accuracy rates for the model were determined for different levels of misclassification costs. Unfortunately, in the context of different types of business using failure prediction models to assess the non-failed status of firms, misclassification costs are largely unknown. Analysts who consider costs typically provide results for a wide range of costs specifications. This was done in the research of Altman, Haldeman, and Narayanan [1977], Frydman, Altman, and Kao [1985]. In practice, the cost of misclassifying failed firms as non-failed is likely to exceed the cost of misclassifying non-failed firms as failed. The expected misclassification costs of using the model were computed for five different cutoff points, corresponding to the ratio of CI to CII ranging from 1:1 to 40:1. (Where CI is the cost of a type I error and CII the cost of a type II error). This range was selected because the misclassification cost of a Type I error is expected to be higher than that of a Type II error (i.e. CI > CII), hence, the ratio 1:1 is a lower limit. Further, Taffler [1982] estimated Type I error cost as being some 40 times greater than the Type II error. Hence, 40:1 is an upper limit in this study. These choices are admittedly arbitrary since misclassification costs are likely to be user- and situation-specific. The results are therefore merely suggestive of the relative performance of the respective models and their sensitivity to a change in the classification criterion. The results of the ex post sample are presented in Table 7-11

The computation of the relative costs of misclassification of the various models are show in Table 7-12. These calculations assume prior probability of failure of 3% (see: sub-chapter 5.5). The classificatory power of each of the models was statistically significant, compared to the respective proportional chance criterion. It should be noted that the observed classification accuracy of a model will change with the new cutoff point [Altman, etc. 1977]. For example, in Table 7-12, with the cutoff point of -1.17, the number of type I errors decreases from 5 (13.89%) to 3 (8.33%) while the type II errors increases from 3 (4.17%) to 4 (5.56%). These new estimates will form the basis of comparison along with the more realistic priors and measures of error costs. The definition of cutoff score is the ln $(q_1 C_I / q_2 C_{II})$.

The following calculations represent our efficiency comparison tests based on the CI:CII = 10:1:

$$
\begin{aligned}
EC_{IRR1} &= q_1 (n_{12} / n_1) CI + q_2 (n_{21} / n_2) CII \\
&= 0.03 (5/36)*10 + 0.97 (3/72)*1 \\
&= 0.081
\end{aligned}
$$

$$
\begin{aligned}
EC_{prop} &= q_1 q_2 CI + q_1 q_2 CII \\
&= (0.03)(0.97)(10) + (0.03)(0.97)(1) \\
&= 0.32
\end{aligned}
$$

Where q_1 and q_2 are the population's prior probabilities of failure and non-failure. n_{ij} is the number of firms of group i misclassified in group j (detail see: chapter 5.5). EC_{prop} (which is defined as $q_1q_2CI + q_1q_2CII$) is a proportional chance strategy based on observed error rates equalling a prior probabilities. Therefore, the best estimates, or most likely results, indicates that $EC_{IRR1} < 3.95EC_{prop}$. That is, the EC_{prop} naive strategies is almost 3.95 times more costly than the EC_{IRR1} model. The other four comparisons tests and their results as listed in Table 7-12. Table 7-12 shows that the IRR1 model is consistently less costly than UR.

The evaluation of relative cost ratios between IRR1 and UR models. Table 7-12 shows that the lowest costs were achieved by the IRR1 model when compared with that of UR model. At the assumed relative cost ratio of one to one, the use of the IRR1 data saves 162 percent relative to the UR model. If the cost ratios is decreased to 10 to one, a IRR1 model would achieve a cost savings of 26 percent over the UR model. Further, at the other three assumed relative cost ratios, use of the IRR1 form outperformed models using the UR form.

Table 7-11 Model Efficiency Comparisons Between IRR1 and UR - Ex Post Sample Classification One Year BF

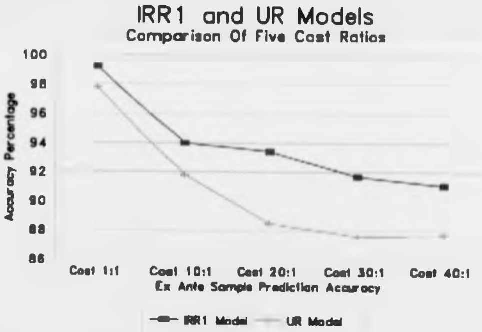
CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1					
Non-failure %	100.0	98	96	93	92
Failure %	52.0	83	85	89	92
Overall %	98.6	94.4	91.8	91.0	92.4
UR					
Non-failure %	99	95	95	91	90
Failure %	63	87	87	90	92
Overall %	98	93.1	91.9	90.8	91.5

Table 7-12 Model Efficiency Comparisons Between IRR1 and UR - Ex Ante Sample Predictions One Year Before Failure

CI:CII (Ratios)	1:1	10:1	20:1	30:1	40:1
IRR1					
Non-failed %	72/72	69/72	68/72	66/72	65/72
Failed %	26/36	31/36	33/36	33/36	33/36
Overall %	99.2	94.0	93.4	91.7	91.1
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{IRR1}	**0.008**	**0.081**	**0.103**	**0.155**	**0.194**
EC_{pop}	0.05	0.32	0.61	0.90	1.19
Times	6.25	3.95	5.92	5.80	6.13
UR					
Non-failed %	71/72	68/72	66/72	64/72	62/72
Failed %	26/36	30/36	30/36	31/36	32/36
Overall %	97.8	91.8	88.5	87.6	87.7
EC_{UR}	**0.021**	**0.103**	**0.18**	**0.232**	**0.267**
Relative Cost Ratios					
IRR1 Model %	100	100	100	100	100
UR Model %	262	126	174	149	137

EC = Expected Cost. EC_{IRR1} = Expected Cost for Industry Mean Ratios.
EC_{UR} = Expected Cost for Unadjusted Ratios. CI = Type I. CII = Type II.
IRR1 = industry Mean Ratios. UR = Unadjusted Ratio

Figure 7-1



7. 2 The Model: - Using Industry Median Ratios (IRR2)

The reasons given for the choice of the industry median ratios (IRR2) are generally related to its robustness to large outliers and measurement errors. One or two outliers firms in a specific industry could distort the measure of central tendency if the industry mean was utilised, especially if the industry has relatively few members.(see: Lev and Sunder, 1979, and Izan, 1984). The following model was developed on the basis of the data of the use of industry median ratios (IRR2) first year before failure (BF). The purpose is to compare its results with the UR model and then to compare them with those of previous studies. For example, Izan [1984] used the median ratios from Australia data to construct a meaningful model in failure prediction area. The results of the discriminant function statistics based upon the ex post sample using discriminant stepwise technique is:

$$Z_{IRR2} = 1.61 + 3.25(FF/CL) - 3.18(NI/NW) - 1.21(OP/TP) + 1.57(TS/NPA) - 1.06(IC/TS)$$

Where :

FF/CL, NI/NW, OP/TP, TS/NPA, and IC/TS are as defined above. Note that these five ratios, we found, are the same as those of IRR1 model based on a stepwise procedure method. The group correlation matrix based on the data of the IRR2 ex post sample are presented in Table 7-13. It shows relationships between all the five variables with some different correlation coefficients. This Table shows that the highest correlation coefficients is (-0.33) between FF/CL and OP/TP. The following are the results of the tests.

7.2.1 Model Significance Test

The statistical significance of the computed function: The computed F-statistic for this function is 52.79 while the tabulated value for F(5,150) = 4.35. The p value for this test is less than 0.001. Thus, this overall function indicate that the constructed model has a good fit and possesses a highly significant discriminating power.

7.2.2 Relative Contribution of Ratios

The relative contribution of each independent variable is presented in Table 7-14. The most important variable is the FF/CL. In fact, the highest ranking ratio (FF/CL) is the same both in IRR1 and IRR2 models. Comparing the coefficients with the IRR1 model from Table 7-3 shows that the results are robust with respect to changing the measure of central tendency from mean to median.

7.2.3 Ex Post and Ex Ante Sample Test

The classificatory power of the IRR2 model is statistically significant compared to the proportional chance model with respect to the percentage of correct classification. In this comparison, we employed sample proportion prior and equal cost ratios. The sensitivity of the results to changing this assumption is discussed below. The IRR2 model is significantly better than the proportional chance criterion, at the 0.001 significance level. Table 7-15 and 7-16 present the classification matrices for the ex post and the ex ante samples, respectively. Table 7-15 shows that the model correctly classified 91% of all the firms in the ex-post sample. Five non-failing firms were misclassified - i.e., type II error of 4.8% (5/104) - and nine failing firms were misclassified - ie., type I error of 17.3% (9/52). The overall error rate is 9% for the ex post sample. The upward bias in the IRR2 model appears to be very slight since the Lachenbruch results are only 1 percent worse. As described above, this classification may be biased upward because of the sampling error. Table 7-16 shows that the model correctly classified 89% of all the firms in the ex-ante sample. Five non-failing and seven failing firms were misclassified, i.e., 7% type II error and 19% type I error. The overall correct classification was 89% of all firms. The overall deterioration between ex post and ex ante sample is only 2%. Table 7-17 shows the comparison of classification results ex post and ex ante example one year BF.

Table 7-13 Within Groups Correlation Matrix - IRR2 Function

Var	NI/NW	OP/TP	TS/NPA	IC/TS
FF/CL	-0.26	-0.33	-0.15	-0.12
NI/NW		0.12	0.15	0.11
OP/TP			0.03	0.18
TS/NPA				-0.15

Table 7-14 Relative Contribution Tests of Each Independent variables - IRR2 Model

Var.	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	2.08	1	48.06	1
IC/TS	-0.79	5	7.36	4
NI/NW	-1.52	2	20.93	3
OP/TP	-1.42	3	22.48	2
TS/NPA	0.91	4	1.16	5

The value of the overall variables D_2 is 7.81

Table 7-15 Classifying the Ex Post Sample, Using IRR2

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	99	5	104
Failed	9	43	52
Error Rates	5%	17%	9%

Table 7-16 Classifying the Ex Ante Sample, Using IRR2

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	67	5	72
Failed	7	29	36
Error Rate	7%	19%	11%

Table 7-17 Comparison of Classification Results Ex Post and Ex Ante Sample One Year BF

Group	Percent Ex-post	Correctly Classified Lachenbruch	Ex-Ante
Overall	91%	90	89%
Failure	83%	83	81%
Non-failed	95%	93	93%

7.2.4 Comparison With Models - Using Unadjusted Ratios (UR)

The accuracy of the models using IRR2 data was compared to that of the UR data which served as a criterion for evaluating accuracy. The UR model discriminant coefficient is the same as the above IRR1 study because the same ratios are used (see 7.1.7). The UR model is statistically significant at the 0.001 level. The Mahalanobis D^2 of UR is 7.76, marginal lower than that of IRR2's (7.76 vs 7.81). We repeated here again in order to compare with the results of IRR2 model. Table 7-7 shows that ex post sample results in 5 non-failed firms being misclassified and 7 failed firms being also misclassified. The percentage of type II errors made by the ex post sample is 4.8% (5/104), and that the type I errors is 13.4% (7/52), the overall errors is 8%. The results, therefore, is slightly more accurate than using IRR2 data (92% vs 91%), although obviously not a statistically significant difference with these sample sizes. However, Table 7-8 examined the predictive ability of unadjusted ratios one year prior to failure in each of the two groups. The forecast validation analysis resulted in 8.3% (6 of 72) non-failed firms being classified and 17% (6 of 36) failed firms being also misclassified. The overall misclassification rate for the UR forecast validation results is 11%.

The comparison between IRR2 and UR measures is made in Table 7-18. This Table shows that the classification accuracy of IRR2 model performed marginally less accurately than UR model in the ex post analysis, and performed the same accuracy in the ex ante analysis. As regards the comparison with Izan's [1984] model, Table 7-19 shows that the ex post analysis of each of the two models performed the nearly identical (9% vs 8%) for the one year before failure and that Izan's model outperformed IRR2 model for the ex ante analysis.

Table 7-18 Comparison of Error Rate Results: IRR2 and UR One Year Before Failure.

	Percent IRR2	Misclassified UR	IRR2 > UR Difference
Ex Post Sample:			
Non-failed	5%	5%	0%
Failure	17%	13%	+ 4%
Overall	9%	8%	+ 1%
Ex-Ante Sample:			
Non-failed	7%	8%	- 1%
Failure	19%	17%	+ 2%
Overall	11%	11%	0%

Table 7-19 Comparison of Classification Results Between This Study (IRR2) and Izan's [1984] One Year Before Failure

Percent	Misclassified [This study] [U.K. 1992]	[Izan] [Australia, 1984]
Ex Post Sample Results:		
Non-failed	5%	11%
Failure	17	6%
Overall	9%	8%
Ex Ante Sample Results:		
Non-failed	7%	0%
Failure	19	0%
Overall	11	0%

7.2.5 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five input misclassification costs is shown in Table 7-20 and 7-21. The comparison between the measures of efficiency is made in Table 7-21. At the assumed relative cost ratio of one to one, use of the IRR2 model saves 75 percent relative to the UR model. If the cost ratio of ten to one, use of the IRR2 model saves only 9 percent relative to the UR model. If the cost ratio is decreased to 20:1, UR model would achieve a same cost savings as IRR2 model. The other two assumed cost ratio of 30:1 and 40:1, use of the UR model saves only 1 and 4 percent relative to the IRR2 model, respectively. We observe that the IRR2 model is more efficient, and this efficient differential ranges from 3.38 to 4.8 times. Table 7-21 shows that the functions under five various input misclassification costs of IRR2 model performed nearly identically when compared with that of UR model one year before failure. The statistical difference between IRR2 and UR models is not significant based on Conover [1971] (defined as in chapter 5) T Test.

Table 7-20 Model Efficiency Comparisons Between IRR2 and UR - Ex Post Sample Classification

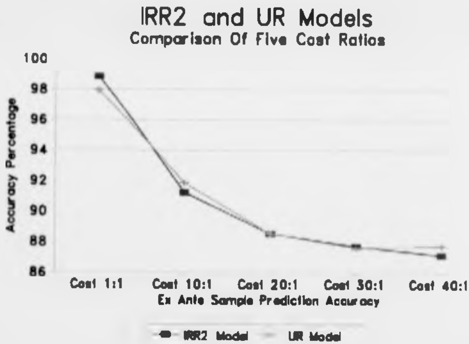
CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2 Model					
Non-failure	100	98	93	92	91
Failure	60	83	85	88	90
Overall	98.8	94.4	90.0	89.5	89.9
UR Model					
Non-failure	99	95	95	91	90
Failure	63	87	87	90	92
Overall	98	93.2	91.9	90.9	91.5

Table 7-21 Model Efficiency Comparisons Between IRR2 and UR - Ex Ante Sample Predictions

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2					
Non-failure	72/72	68/72	66/72	66/72	66/72
Failure	21/36	29/36	30/36	30/36	30/36
Overall %	98.8	91.2	88.5	87.7	87.1
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{IRR2}	**0.012**	**0.094**	**0.18**	**0.23**	**0.28**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.8	3.4	3.38	3.91	4.25
UR					
Non-failure	71/72	68/72	66/72	64/72	62/72
Failure	26/36	30/36	30/36	31/36	32/36
Overall %	97.9	91.8	88.5	87.6	87.7
EC_{UR}	**0.021**	**0.103**	**0.18**	**0.232**	**0.267**
Relative Cost Ratios					
IRR2 Model %	100	100	100	100	104
UR Model %	175	109	100	101	100

IRR2 = Industry Median Ratios
EC_{IRR2} = Expected Cost for Industry Median Ratios

Figure 7-2



7.3 The Model 3: Using the Optimal Unadjusted Ratios (UR)

The following model function was first developed on the basis of the Unadjusted Ratios (UR) data of the first year BF. The purpose is to compare its results with the IRR1 and IRR2 data and then to compare them with those of above studies. The UR's model function based on the initial sample is:

$$Z_{UR} = -5.63 + 0.78(FF/CL) - 1.92(NI/TS) - 0.98(OP/TP) + 2.34(CA/TA) - 1.91(IC/TS)$$

It should be stressed that in the earlier sections, the discriminant models as presented are first derived with IRR1 and IRR2 models. The unadjusted ratios models were then constrained to include the same ratios as in the IRR1 and IRR2 models.In this section, the optimal UR model is first derived with the UR model and then the same ratio composition is imposed on the IRR1 and IRR2 models. Note that it selects a different set of ratios. The relationships between the above five variables are represented by the within groups correlation matrix in Table 7-22. As stated above, negative correlation coefficients increase the discriminating power of the set of independent variables. The above UR function of the first year's model was subjected to the tests as before:

7.3.1 Model Significance Test

The statistical significance of the computed function: The computed F-statistic for this function is 52.52 while the tabulated value for $F(5,150) = 4.35$. The p value for this test is less than 0.001. Thus, this UR function also possesses a highly significant discriminating power.

7.3.2 Relative Contribution of Ratios

The relative contribution of each ratio is shown in Table 7-23. The ranking between standardized discriminant coefficients and Mosteller and Wallace's two methods is nearly identical. We see that FF/CL, CA/TA and IC/TS are consistently ranked in relative contribution between failed and non-failed groups. The highest ranking in the UR model is FF/CL again. However, the value of the overall D^2 is 7.77.

7.3.3 Ex Post and Ex Ante Sample Test

The classificatory power of the UR model is statistically significant from the proportional chance criterion. In this comparison, the Z-value is 7.87 for the proportional chance model, significant at the 0.001 significance level. Table 7-24 and Table 7-25 present the classification tables for the ex post and the ex ante samples, separately. Table 7-24 shows that the model correctly classified 92% of all the firms in the ex-post sample. Type I error is 15.3% (8 of 52) and type II error is 4% (4 of 104). Table 7-25 shows that the percentage of firms correctly classified in the ex ante sample model. The type I error is 22% (8 of 36) and type II error is 10% (7 of 72). The overall misclassification rate for the unadjusted ratios forecast validation results is 14%. Table 7-26 presents the percentage of companies correctly classified ex post and ex ante by both models overall and broken down by status of the company. The results of the forecast validation test display the unstable classification accuracy identified in previous research. The deterioration between ex post and ex ante sample is 6%. The result for the Lachenbruch validation sample bias test is identical to the original sample (92% vs 92%), indicating that the results are not sensitive to sample bias.

Table 7-22 Within Groups Correlation Matrix - UR Function

Variable	NI/TS	OP/TP	CA/TA	IC/TS
FF/CL	0.11	-0.43	-0.04	-0.45
NI/TS		-0.19	-0.04	-0.15
OP/TP			0.01	0.40
CA/TA				-0.10

Table 7-23 Relative Contribution Tests of Each Independent Variables - UR Model

Var.	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	2.08	1	56.03	1
NI/TS	-1.15	3	2.00	4
OP/TP	-1.09	4	17.56	3
CA/TA	0.32	5	1.00	5
IC/TS	-1.27	2	23.73	2

The Value of the overall variables D^2 is 7.77

Table 7-24 Classifying the Ex Post Sample - Using UR One Year BF

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	100	4	104
Failed	8	44	52
Error Rates %	4%	15%	8%

Table 7-25 Predicting the Ex Ante Sample - Using UR One Year BF

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	65	7	72
Failed	8	28	36
Error Estimate %	10%	22%	14%

Table 7-26 Comparison Between The Ex Post and Ex Ante Analysis - Using UR One Year BF

Groups	Percent Ex-post	Correctly Lachenbruch	Classified Ex-Ante	ExPost > ExAnte Difference
Non-failed	96%	96%	90%	+ 6%
Failure	85%	85%	78%	+ 7%
Overall	92%	92%	86%	+ 6%

7.3.4 Comparison With Models - Using Industry Mean Ratios (IRR1)

The IRR1 ratio model is then constrained to include the same five ratios as in the unadjusted ratios model. Table 7-27 shows that ex post sample results in 6 non-failed firms being misclassified and 5 failed firms being also misclassified. The percentage of type II errors made by the ex post sample is 6% (6 of 104), and that the type I errors is 10% (5 of 52). The overall misclassification for the IRR1 data is 7%. Table 7-29 shows that the IRR1 model outperformed UR model for the first year BF. However, Table 7-28 shows that the forecast validation analysis resulted in 6% (4 of 72) non-failed firms being classified and 14% (5 of 36) failed firms being misclassified. Table 7-29 shows that the IRR1 model is superior to the UR model in the forecast validation results.

Table 7-27 Classifying the Ex Post Sample, Using IRR1 Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	98	6	104
Failed	5	47	52
Error Estimate %	6%	10%	7%

Table 7-28 Predicting the Ex Ante Sample, Using IRR1 Model

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	68	4	72
Failed	5	31	36
Error Estimate	6%	14%	8%

Table 7-29 Comparison of Error Rate Results: UR and IRR1 One Year BF.

	Percent IRR1	Error Classified UR	UR > IRR1 Difference
Ex Post Sample			
Non-failed	6%	4%	- 2%
Failure	10%	15%	+ 5%
Overall	7%	8%	+ 1%
Ex Ante Sample			
Non-failed	6%	10%	+ 4%
Failure	14%	22%	+ 8%
Overall	**8%**	**14%**	**+ 6%**

7.3.5 Comparison With Models - Using Industry Median Ratios (IRR2)

The accuracy of the models using IRR2 data was compared to that of the UR data which served as a criterion for evaluating accuracy. The IRR2 model is statistically significant at the 0.001 level. Thus, the overall discriminating power of the IRR2 function is highly significant. The same five ratios as UR model were used. The model's function fitted to the within-sample follow as:

$$Z_{IRR2} = 2.06 + 3.23FF/CL - 1.61NI/TS - 1.02OP/TP + 4.63CA/TA - 1.05IC/TS$$

Table 7-30 shows that ex post sample results in 7 non-failed firms being misclassified and 5 failed firms being also misclassified. The percentage of type II errors made by the ex post sample is 7% (7 of 104) and type I errors is 10% (5 of 52). The overall misclassification for the IRR2 is 8%. Table 7-31 shows that IRR2 model outperformed UR model only by 2% one year BF with respect to classification accuracy. The forecast validation analysis resulted in 8% [6 of 72] non-failed firms being classified and 17% [6 of 36] failed firms being also misclassified. The overall misclassification rate for the IRR2 forecast validation results is 11%. The comparison between IRR2 and UR measures is made in Table 7-32. This Table shows that the industry median model performed better than the unadjusted model one year prior to failure.

Table 7-30 Classifying the Ex Post Sample, Using IRR2 Model One Year Before Failure

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	97	7	104
Failed	5	47	52
Error Estimate	7%	10%	8%

Table 7-31 Predicting the Ex Ante Sample, Using IRR2 Model One Year Before Failure

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	66	6	72
Failed	6	30	36
Error Estimate	8%	17%	11%

Table 7-32 Comparison of Error Rate Results Between UR and IRR2 One Year Before Failure

Percent	Error IRR2	Classified UR	UR > IRR2 Difference
Ex Post Sample			
Non-failed %	7	4	- 3%
Failure %	10	15	+ 5%
Overall %	8	8	+ 0%
Ex Ante Sample			
Non-failed %	8	10	+ 2%
Failure %	17	22	+ 5%
Overall %	11	14	+ 3%

7.3.6 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 7-33 and Table 7-34. At the assumed relative cost ratio from 1:1 to 40:1 (see: section 7.1.9), with the UR model cost ratios of 10:1, the number of type I errors decreases from 8 (22%) to 7 (19.4%) while type II errors increases from 5 (6.9%) to 10 (13.9%). With the IRR1 model, the number of type I errors decreases from 6 (16.6%) to 5 (13.8) while the type II errors increases from 3 (4.1%) to 11 (15.2%). With the IRR2 model, the number of type I errors decreases from 9 (25%) to 5 (13.8%) while the type II errors increases from 4 (5.5%) to 5 (13.8%). The classificatory power of each of the five difference choice cost ratio models was significantly better than the respective proportional chance model. Type I misclassification decreases when the cost ratio increases, and the type II misclassification increases when the cost ratio increases. The reason for this behaviour has been described in chapter 7.1.9. These new estimates will form the basis of comparison along with the more realistic priors and measures of error costs. At the assumed relative cost ratio of one to one, use of the IRR1 saves 120 percent relative to the best UR model. If the cost ratio is changes to 10 to one, a user would achieve a cost savings of 212 percent over the best IRR2 model. However, if the cost ratios changes to 30:1 and 40:1, use of the IRR2 model saves 12 and 15 percent respectively to the best IRR1 model. The combined UR model was inferior to the IRR1 and IRR2 models in these comparisons (see Table 7-34).

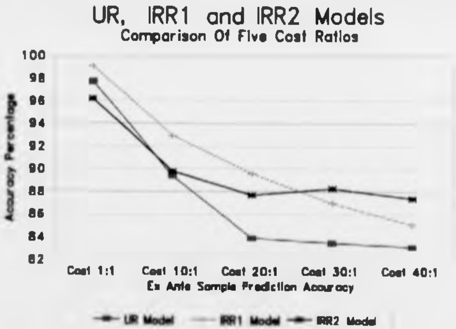
Table 7-33 Model Efficiency Comparisons Among UR, IRR1 and IRR2 - Ex Post Classification

CI:CII	1:1	10:1	20:1	30:1	40:1
UR					
Non-failed	99	97	96	94	92
Failed	60	83	87	88	90
Overall Accuracy	97.9	93.7	92.5	91.5	91.3
IRR1					
Non-failed	99	96	93	91	89
Failed	42	85	92	94	94
Overall	97.4	93.4	93.0	92.3	91.7
IRR2					
Non-failed	99	95	92	91	89
Failed	42	85	90	92	92
Overall	97.3	92.8	91.6	91.9	91.1

Table 7-34 Model Efficiency Comparisons Among UR, IRR1 and IRR2 - Ex Ante Predictions

CI:CII	1:1	10:1	20:1	30:1	40:1
UR					
Non-failed	71/72	67/72	63/72	62/72	62/72
Failed	25/36	28/36	28/36	29/36	29/36
Overall %	97.7	89.4	83.9	83.5	83.1
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{UR}	**0.022**	**0.133**	**0.254**	**0.309**	**0.367**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	2.63	2.40	2.40	2.91	3.24
IRR1					
Non-failed	72/72	69/72	66/72	63/72	61/72
Failed	24/36	30/36	31/36	31/36	31/36
Overall %	99	92.9	89.6	87.0	85.1
EC_{IRR1}	**0.01**	**0.041**	**0.163**	**0.246**	**0.314**
IRR2					
Non-failed	70/72	68/72	65/72	65/72	64/72
Failed	22/36	27/36	30/36	31/36	31/36
Overall %	96.2	89.8%	87.7	88.3	87.4
EC_{IRR2}	**0.037**	**0.128**	**0.194**	**0.219**	**0.273**
Relative Cost Ratios					
UR %	220	324	155	141	134
IRR1 %	100	100	100	112	115
IRR2 %	370	312	119	100	100

Figure 7-3



7.4 Comparison of the Three Optimal Models - UR, IRR1 and IRR2

The first following three hypotheses tests in this chapter are:

H_1: There is no difference in the predictive abilities of financial ratios between the industry mean ratios (IRR1) and the model of unadjusted ratios (UR) in the ex ante sample.

H_2: There is no difference in the predictive abilities of financial ratios between the industry median ratios (IRR2) and the model of unadjusted ratios (UR) in the ex ante sample.

H_3: There is no difference in the predictive abilities of financial ratios between the industry mean ratios (IRR1) and the model of industry median ratios (IRR2) in the ex ante sample.

The results of the discriminant analyses using the three different models based on sample proportion prior and equal cost described above are re-presented in Table 7-35. IRR1 produces the most stable rate of classification ex post rate to ex ante rate is 93% to 93% showing no diminution in accuracy. For IRR2 the rates are 91% to 89%, and for UR the Platt and Platt observation is seen again with the rate failure from 92% down to 86% when comparing initial to hold-out. The IRR1 model does a consistently better job of classifying and predicting the companies in both the ex post sample and ex ante sample.

The data is repeated to determine the extent to which ex ante predictive ability was affected if the objective was minimizing the relative costs of misclassification. The results are therefore merely suggestive of the relative performance of the respective models and their sensitivity to a change in the classification criterion. The results of the analyses are presented in Table 7-36A. Table 7-36A below shows the result of testing H_1. Relative costs for IRR1 are always lower than UR model. The statistical Conover [1971] T test are consistently significant at the different levels when the cost ratios are 10:1, 20:1, 30:1 and 40:1, respectively. The IRR1 model is superior to UR model with respect to every combination of expected cost and CI:CII; except that of CI:CII = 1:1, but this is not statistically significant. It appears that the null hypotheses H_1, which relate to IRR1 and UR ratios, as states above, can be rejected for the ex ante example only in some certain cases, very large sample sizes are required in order to measure differences in error rates with precision. Table 7-36b below shows the result of testing H_2. IRR2 is not significantly different from UR, but the percentage of correct classification of IRR2 is higher than UR. Also relative costs for IRR2 are lower than those for UR. Based on these results, the null hypotheses H_2 cannot be rejected. Table 7-36c below shows the result of testing H_3. IRR1 is not statistically different from IRR2, but the percentage of correct classification is slightly higher than IRR2. Relative costs from IRR1 are lower than those of IRR2. From the results and findings , the null hypotheses H_3 can not be rejected.

Table 7-35 Results of the Three Best Models - UR, IRR1 and IRR2

Model And	Non-failed	Failed	Total
Ex Post (Initial) Sample Classification			
UR Model	100/104	44/52	156
	96%	85%	92%
IRR1 Model	100/104	44/52	156
	96%	85%	93%
IRR2 Model	99/104	43/52	156
	95%	83%	91%
Ex Ante (Hold-out) Sample Prediction			
UR Model	65/72	28/36	108
	90%	78%	86%
IRR1 Model	68/72	32/36	108
	94%	89%	93%
IRR2 Model	67/72	29/36	108
	93%	81%	89%

7-36A Model Efficiency Comparisons Between the Best UR and IRR1 Models - Ex Ante Predictions

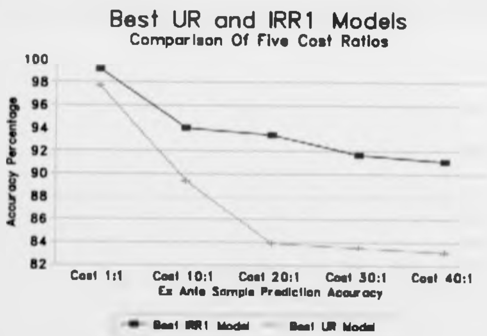
CI:CII	1:1	10:1	20:1	30:1	40:1
UR					
EC_{UR}	**0.022**	**0.133**	**0.254**	**0.309**	**0.367**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	2.63	2.40	2.40	2.91	3.24
IRR1					
EC_{IRR1}	**0.008**	**0.081**	**0.103**	**0.155**	**0.194**
EC_{prop}	0.05	0.32	0.61	0.90	1.19
Times	6.25	3.95	5.92	5.80	6.13
Relative Cost Ratios					
UR %	275	164a	246d	199c	189b
IRR1 %	100	100a	100d	100c	100b
T Test					
T-Value	0.20	1.3a	4.688d	2.798c	2.07b
Significance	0.653	0.25	0.03	0.094	0.15

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$

c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

(see section 5.7, p.185 : the null hypothesis is rejected.)

Figure 7-4

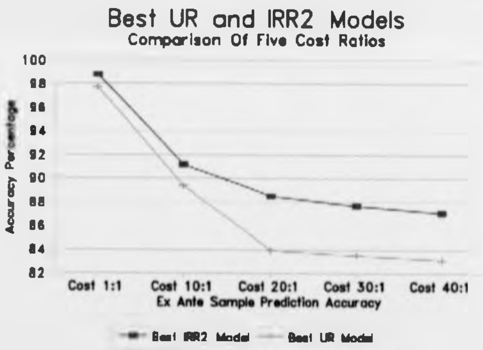


7-36B Model Efficiency Comparisons Between the Best UR and IRR2 Models - Ex Ante Predictions

CI:CII	1:1	10:1	20:1	30:1	40:1
UR					
EC_{UR}	**0.022**	**0.133**	**0.254**	**0.309**	**0.367**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	2.63	2.40	2.40	2.91	3.24
IRR2					
EC_{IRR2}	**0.012**	**0.094**	**0.18**	**0.23**	**0.28**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.8	3.4	3.38	3.91	4.25
Relative Cost Ratios					
UR %	183	140	141	134	131
IRR2 %	100	100	100	100	100
T Test					
T-Value	0.381	0.188	0.996	0.996	0.996
Significance	0.537	0.665	0.318	0.318	0.318

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$
c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

Figure 7-5



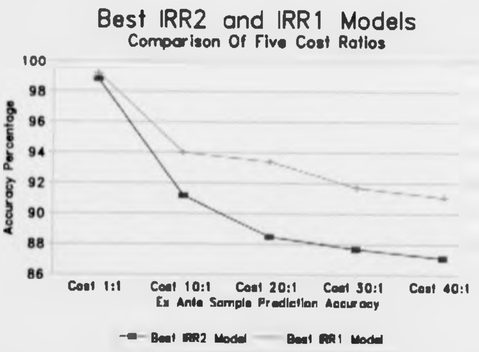
7-36C Model Efficiency Comparisons Between the Best IRR1 and IRR2 Models - Ex Ante Predictions

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1					
EC_{IRR1}	**0.008**	**0.081**	**0.103**	**0.155**	**0.194**
EC_{prop}	0.05	0.32	0.61	0.90	1.19
Times	6.25	3.95	5.92	5.80	6.13
IRR2					
EC_{IRR2}	**0.012**	**0.094**	**0.18**	**0.23**	**0.28**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.8	3.4	3.38	3.91	4.25
Relative Cost Ratios					
IRR1 %	100	100	100	100	100
IRR2 %	150	117	174	148	144
T Test					
T-Value	1.131	0.519	1.443	0.475	0.475
Significance	0.288	0.471	0.23	0.491	0.491

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$

c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

Figure 7-6



7.4.1 Results Two and Three Years Prior - Using UR Model

The whole analysis can be repeated to explore the ability of the models to classify more than one year prior to failure. The overall UR model was statistically significant at better than $\alpha = 0.001$ two and three years before failure, respectively. As expected, with the cost ratios 10:1, the Type I accuracy falls from the 83% one year prior to 67% two year prior and 56% three year prior. Type II accuracy does not fall monotonously 97% one year down to 92% two years and 95% three years. The overall accuracy falls from the 94% one year prior to 86% two years prior and 86% three years prior. Table 7-37 and Table 7-38 repeats the model efficient comparisons under five various error costs ex post classification and ex ante prediction results.

Table 7-37 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Two Years BF, Using UR

Years BF	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	92	89	87	86
Ex Post	Failed	15	67	77	85	85
Sample	Overall %	97	86	85	86	85
2	Non-failed	100	83	75	69	63
Ex Ante	Failed	41	75	78	86	92
Sample	Overall %	98	81	76	77	79

Table 7-38 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Three Years BF, Using UR

Years BF	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	95	82	75	69
Ex Post	Failed	2	56	79	85	88
Sample	**Overall %**	**97**	**86**	**81**	**79**	**80**
3	Non-failed	100	81	60	54	48
Ex Ante	Failed	13	67	86	87	89
Sample	**Overall %**	**97**	**78**	**70**	**69**	**70**

7.4.2 Results Two and Three Years Prior - Using IRR1 Model

The overall IRR1 model was statistically significant at better than $\alpha = 0.001$, two and three years BF. As expected, with the cost ratios of 10:1, the type I error increases from the 17% one year prior to 31% two years prior and 36% three years prior, type II error increases from 2% one year prior to 7% two years prior and 9% three years prior. Table 7-39 and Table 7-40 present model efficiency tests under five different error costs between ex post and ex ante analysis. More stable classification rates for second and third year before failure are seen again.

Table 7-39 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Two Years BF, Using IRR1

Years Priors	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	93	87	81	78
Ex Post	Failed	13	69	79	88	90
Sample	**Overall %**	**97**	**87**	**84**	**84**	**85**
2	Non-failed	100	90	81	72	67
Ex Ante	Failed	39	72	83	83	86
Example	**Overall %**	**98**	**86**	**82**	**78**	**77**

Table 7-40 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Three Years BF, Using IRR1

Years BF	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	91	78	71	64
Ex Post	Failed	0	64	74	87	91
Example	**Overall %**	**97**	**86**	**77**	**78**	**79**
3	Non-failed	100	91	86	73	72
Ex Ante	Failed	14	60	64	64	64
Sample	**Overall %**	**97**	**79**	**78**	**69**	**69**

7.4.3 Two and three Years Prior - Using Industry Median Ratios (IRR2)

The sensitivity of the results to changing the definition of the industry average from the mean to the median can be examined. The overall IRR2 model efficient test shows that $EC_{IRR2} < EC_{prop}$. That is, the proportional chance criterion is less efficient than EC_{IRR2} model. As expected, with the cost ratios of 10:1, the type I error increases from 17% one year prior to 25% two years prior and 62% three years prior. type II error increases from 2% one year prior to 7% two years prior and 7% three years prior. The overall accuracy falls from the one year 94.4% to 89% and 80% in year two and three. Table 7-41 and Table 7-42 repeats the model efficient comparisons under five various costs ex post and ex ante prediction results.

Table 7-41 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Two Years BF, Using IRR2

Years BF	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	93	90	87	85
Ex Post	Failed	13	75	79	81	85
Sample	**Overall %**	**97**	**89**	**86**	**84**	**85**
2	Non-failed	97	85	83	72	91
Ex Ante	Failed	36	78	83	86	100
Example	**Overall %**	**95**	**83**	**83**	**80**	**96**

Table 7-42 Model Efficiency Comparisons Between Ex Post and Ex Ante Sample Three Years BF, Using IRR2

Years BF	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	93	87	82	73
Ex-Post	Failed	3	38	58	73	81
Sample	**Overall %**	**97**	**80**	**76**	**78**	**78**
3	Non-failed	100	92	83	77	72
Ex Ante	Failed	4	38	50	61	64
Sample	**Overall %**	**94**	**79**	**71**	**70**	**68**

7.5 Summary and Conclusions

As concluded above, the industry mean ratios (IRR1) model compared with UR model, the correctly classified 93 per cent of the companies, performing better than the unadjusted model particularly in the forecast validation result one year prior to failure (93% vs 86%) (see: Table 7-35). This result is based upon prior failure rates being in the sample proportion and equal error costs. When incorporating realistic prior probability and five various cost assumptions are accounted for, the optimal IRR1 model dominates the optimal UR model (see: Table 7-36A).

When using the optimal industry median Ratios (IRR2) model and comparing with optimal UR model, the results show that the optimal IRR2 dominates the optimal UR UR model (89% vs 86%) in the ex ante sample based on the sample prior proportion and equal error cost (see: Table 7-35). When incorporating realistic prior probability and five various cost assumption are accounted for, the results show that the IRR2 model marginally dominates the UR model (see: Table 7-36B).

Comparing the industry mean ratios (IRR1) model with industry median ratios (IRR2) model, the IRR1 form performed better than the IRR2 model in forecast validation result one year prior to failure (93% vs 89%). This is based on the sample prior proportions and equal error costs (see: Table 7-35). When incorporating realistic prior probability and five various cost assumptions are accounted for, the optimal IRR1 model dominates the optimal IRR2 model (see: Table 7-36C).

When incorporating the realistic prior probability and different relative misclassification costs, the results of analyses still show that the best IRR1 model dominates the best IRR2 and UR models at different misclassification costs ranging from 1:1 to 40:1 (see: Table 7-36A, Table 7-36b, and Table 7-36C). The best UR model is somewhat sensitive to the cost ratio and/or the prior probability when compared with the best IRR1 and IRR2 models (see Table 7-36A, 7-36B, and 7-36C). Expected cost performance from UR, IRR1, and IRR2 models are all much lower than those from the proportional chance model when the misclassification costs ranging from 1:1 to 40:1.

Platt and Platt (1990) indicated that failure models generally produce lower classification levels with out of sample data than within-sample data. Using a simple - test for the difference between proportions for the overall percentage correctly classified, in this study we confirm their results with six of the twelve comparisons yielding significantly lower proportions for out-of-sample classification compared to within-sample classification.

In this study, we used 264 firms covering 11 years time span and 16 industries to examine whether using industry relative (mean and median) ratios can solve the instability problem. We concluded, based on our empirical results, that industry relative (mean) ratios are expected to provide several benefits over unadjusted ratios when used to predict corporate failure.

However, as we have mentioned, Barnes [1990] states that there are many reasons why the model may not be stable over time, and it may not be sufficient to merely take into account an industry effect but also consider the variation in economic environment. In the next chapter 8, we will examine the stability of the models for various ratios forms with respect to the business cycles.

Chapter 8 Empirical Results of Business Cycle

8.1 Introduction

Whilst previous studies were interested in the predictive value of the functions they derived, few examined the performance of their function for time periods outside of those used to develop the models initially. One possible source of instability in multivariate models of failure might be an impact by different macro-economic environments. The rates of corporate failure rise quickly during economic recession. Mensah [1984], Wood and Piesse [1987] have suggested that data instability which is due to changes in inflation, interest rates and phases of the business cycles may be responsible for the differences in classification results between estimation and forecast periods. This chapter uses industry relative ratios (across industries) and considers homogeneous business cycle (time series) simultaneously to see how important this factor is in explaining instability in the models. In this chapter, the bankrupt companies used in this study are divided into three sub-periods based on the degree of movement of the three macro-economic variables (inflation rate, interest rate, and real GNP) (see Table 6-15). The breakdown of the sample according to these sub-periods is given at section 6.6.3.

The total sample was divided into three groups consisting of 15, 36 and 37 pairs rather than using a hold-out sample. The samples were aggregated. The three aggregate models (UR, IRR1 and IRR2) and three separate economic conditions models (Expansion, Recession and Recovery) were explored in subsequent discriminant analysis. The structure of this chapter is inevitably repetitive, since by stratifying the sample by time period we multiply the number of models to develop, evaluate and compare. The scheme of testing employed may be represented by the following chart:

Time			Periods						
Aggregate	Expansionary			Recessionary			Recovery		
AG	B1 UR	B1 IRR1	B1 IRR2	B2 UR	B2 IRR1	B2 IRR2	B3 UR	B3 IRR1	B3 IRR2
	(8.5)	(8.6)	(8.7)	(8.8)	(8.9)	(8.10)	(8.11)	(8.12)	(8.13)
UR (8.2)	√	√	√	√	√	√	√	√	√
IRR1 (8.3)		√			√			√	
IRR2 (8.4)			√			√			√

Where UR = Unadjusted Ratios
IRR1 = Industry (mean) Relative Ratios
IRR2 = Industry (median) Relative Ratios
(8.2) = Section Number
√ = Pairwise - Comparison of Models

The testing strategy for every model follows the routine:

(1) Use SAS stepwise discriminant procedure to identify an optimal discriminant model, reporting ratios, and their relative contribution to discriminatory power.

(2) Compare the classificatory accuracy of the model to proportional chance criterion. Also validate using Lachenbruch hold-out.

(3) Explore the sensitivity of the models to variation in prior probability and misclassification costs.

16 models are developed in this chapter, and they are coded as follows

Time Period	AG	B1	B2	B3
Ratio Form				
UR	URAG	URB1	URB2	URB3
IRR1	IRR1AG	IRR1B1	IRR1B2	IRR1B3
IRR2	IRR2AG	IRR2B1	IRR2B2	IRR2B3

In this chapter we will be examining hypotheses from H_4 to H_{18} listed in chapter one. the final section of this chapter (8.14) presents a summary.

8.2 The Aggregate Model - Using Unadjusted Ratios (UR_{AG})

The unadjusted ratios aggregate model's function based upon the entire sample is:

Z_{URAG}=3.69+1.83(FF/CL)-1.09(NI/TS) - 0.94(OP/TP) + 0.44(CA/TA) - 1.26(IC/TS).

The statistical significance of the computed function: The computed F-statistic for this function is 77.92 while the tabulated value for while the tabulated value for $F(5,258) = 4.25$ for $\alpha = 0.001$. Thus, this aggregate UR function possesses a highly significant discriminating power. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the unadjusted ratios combined sample, in Table 8-1.

8.2.1 Relative Contribution of Ratios

The relative contribution of each ratio is shown in Table 8-2. We see that FF/CL and IC/TS are consistently ranked in relative contribution between failed and non-failed groups. The highest ranking in the URAG model is FF/CL again. However, the value of the overall D^2 is 6.74.

8.2.2 Examining the Classification Accuracy Test

The classificatory power of the URAG model is statistically significant different to the proportional chance criterion. The test statistic for the difference between the results and proportional chance is 10.9, with 0.001 significance level. Table 8-3 presents the classification rates for the combined sample. Table 8-4 shows that the model correctly classified 91% of all the firms in the combined sample. Type II error is 5.1% (17 of 88) and type I error is 18.1% (10 of 176). The result for the Lachenbruch validation sample bias test is only one percent worse to the original sample (91% vs 90%).

Table 8-1 Groups Correlation Matrix - URAG Function

Var	NI/TS	OP/TP	CA/TA	IC/TS
FF/CL	0.06	-0.41	-0.07	-0.44
NI/TS		-0.07	-0.04	-0.08
OP/TP			0.04	0.38
CA/TA				-0.05

Table 8-2 Relative Contribution Tests of Each Independent Variables - URAG Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	1.83	1	76.90	1
NI/TS	-1.09	3	1.50	4
OP/TP	-0.94	4	10.00	3
CA/TA	0.44	5	1.00	5
IC/TS	-1.26	2	10.60	2

The Value of the overall variables D^2 is 6.74

Table 8-3 Classifying the Aggregate Sample - Using URAG One Year BF

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	166	10	176
Failed	17	71	88
Error Rates %	5.1%	18.1%	9.4%

8.2.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 8-4. At the assumed relative cost ratio from 1:1 to 40:1, with the URAG combined model cost ratios of 10:1, the number of type I errors decreases from 26% to 17% while type II errors increases from 4% to 6%. Type I misclassification decreases when the cost ratio increases, and the type II misclassification increases when the cost ratio increases. Table 8-5 shows that the URAG aggregate model is consistently less costly than proportional chance criterion.

8-4 Model Efficiency Comparisons - Using URAG Aggregate Sample.

CI:CII	1:1	10:1	20:1	30:1	40:1
URAG					
Non-failed	100	96	94	93	91
Failed	59	74	83	83	86
Overall Accuracy	98.8	90.7	90.0	88.0	88.5

8-5 Model Efficiency Comparisons - Using URAG Aggregate Lachenbruch Validation Test

CI:CII	1:1	10:1	20:1	30:1	40:1
URAG					
Non-failed	175/176	168/176	165/176	162/176	159/176
Failed	51/88	65/88	73/88	73/88	74/88
Overall %	98.2	90.3	89.7	87.7	86.9
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	3.22	2.66	3.81	3.91	4.25

8.3 The Aggregate Model - Using Industry Mean Ratios (IRR1)

The IRR1 aggregate model's function based upon the combined sample is:

$$Z_{IRR1AG} = 4.89+4.86(FF/CL)-4.47(IC/TS)-1.94(NI/NW)+0.90(OP/TP)+0.72(TS/NPA).$$

The statistical significance of the computed function: The computed F-statistic for this function is 88.04 while the tabulated value for while the tabulated value for $F(5,258) = 4.25$ for $\alpha = 0.001$. Thus, this aggregate IRR1AG function possesses a highly significant discriminating power. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the industry mean combined sample, in Table 8-6.

8.3.1 Relative Contribution of Ratios

Table 8-7 presents the relative contribution of the each variables. The discriminant function is consistent according to the standardized coefficients ranking and Mosteller and Wallace method across all ratios.

8.3.2 Examining the Classification Accuracy Test

The classification accuracy is given in Table 8-8. The resulted in 4 non-failed firms being misclassified from 176 non-failed firms and 14 failed firms being misclassified from 88 failed firms. The Type II error is 2.2% (4 of 176) and the Type I error is 15.9% (14 of 88). Overall, the accuracy is 93.2% (246 of 264). The classificatory power of the IRR1AG model is statistically significant compared to the proportional chance model. The test statistic for the difference between the results and proportional chance is 11.57. This has a normal distribution, with 0.001 significance level. The result for the Lachenbruch cross-validation bias test is exactly identical to the original sample (93% vs 93%), indicating that the results are not sensitive to sample bias.

Table 8-6 Within Groups Correlation Matrix - IRR1AG Aggregate Function

Ratios	IC/TS	NI/NW	OP/TP	TS/NPA
FF/CL	-0.43	-0.37	-0.35	-0.13
IC/TS		0.24	0.39	-0.10
NI/NW			0.24	-0.04
OP/TP				-0.02

Table 8-7 Relative Contribution Tests of Each Independent Variables - IRR1AG Aggregate Model

Var	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	1.65	1	28.02	1
IC/TS	-1.16	3	11.53	3
NI/NW	-1.29	2	31.04	2
OP/TP	-0.88	4	27.74	4
TS/NPA	0.51	5	1.64	5

The Value of the overall variables D2 is 7.61

Table 8-8 Classifying the Aggregate Sample, Using IRR1AG

Actual Groups	Classified Non-failed	As: Failed	Total
Non-failed	172	4	176
Failed	14	74	88
Error Rates %	2.2%	15.9%	6.8%

8.3.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 8-9. At the assumed relative cost ratio from 1:1 to 40:1, with the IRR1AG aggregate model cost ratios of 10:1, the number of type I errors decreases from 44% (1:1) to 19% (10:1) while type II errors increases from 0% to 2%. Type I misclassification decreases when the cost ratio increases, and the type II misclassification increases when the cost ratio increases. Table 8-10 shows that the IRR1AG aggregate model is consistently less costly than proportional chance criterion ranging from 4.0 to 5.95 times.

8-9 Model Efficiency Comparisons - Using IRR1AG Aggregate Sample.

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1AG Aggregate Model					
Non-failed	100	98	97	95	93
Failed	56	81	86	89	90
Overall Accuracy	98.7	94.1	93.1	92.2	91.4

8-10 Model Efficiency Comparisons - Using IRR1AG Aggregate Lachenbruch Validation Test

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1AG Aggregate Model					
Non-failed	176/176	172/176	169/176	166/176	164/176
Failed	48/88	71/88	75/88	77/88	78/88
Overall %	98.7	93.7	92.0	91.1	90.7
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{IRR1AG}	**0.013**	**0.08**	**0.12**	**0.17**	**0.20**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.46	4.00	5.08	5.29	5.95

8.4 The Aggregate Model - Using Industry Median Ratios (IRR2)

The IRR2 aggregate model's function based upon the combined sample is:

Z_{IRR2AG} =4.89+4.86(FF/CL)-4.47(IC/TS)-1.94(NI/NW)+0.90(OP/TP) + 0.72(TS/NPA).

The statistical significance of the computed function: The computed F-statistic for this function is 84.11 while the tabulated value for while the tabulated value for $F(5,258) = 4.25$ for $\alpha = 0.001$. Thus, this aggregate IRR2AG function possesses a highly significant discriminating power. Each variables contributed significantly to the model at least better than $\alpha = 0.05$. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the industry median combined sample, in Table 8-11. The relationship between all the five variables with some different correlation coefficients. This Table shows that the highest correlation coefficients is (-0.35) between FF/CL and OP/TP.

8.4.1 Relative Contribution of Ratios

The relative contribution of each independent variable is presented in Table 8-12. The most important variable is the FF/CL. In fact, the highest ranking ratio (FF/CL) is the same both in IRR1AG and IRR2AG models.

8.4.2 Examining the Classification Accuracy Test

The IRR2AG aggregate model is significantly better than the proportional chance criterion. The test statistic for the difference between the results and proportional chance is 10.9. This has a normal distribution, with 0.001 significance level. Table 8-13 presents the classification matrices for the IRR2AG combined samples. Table 8-13 shows that the model correctly classified 91% of all the firms in the combined sample. Eight non-failing firms were misclassified - i.e., type II error of 4.5% (8/176) - and sixteen failing firms were misclassified - ie., type I error of 18.1% (16 of 88).

The overall accuracy rate is 91%. The result for the Lachenbruch validation sample bias test is identical to the original sample (91% vs 91%), indicating that the results are not sensitive to sample bias.

Table 8-11 Groups Correlation Matrix - IRR2AG Aggregate Function

Var	NI/NW	OP/TP	TS/NPA	IC/TS
FF/CL	-0.23	-0.35	-0.15	-0.12
NI/NW		0.16	0.08	0.07
OP/TP			-0.01	0.12
TS/NPA				-0.04

Table 8-12 Relative Contribution Tests of Each Independent Variables - IRR2AG Aggregate Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	2.08	1	48.06	1
NI/NW	-1.52	2	20.93	3
OP/TP	-1.42	3	22.48	2
TS/NPA	0.91	4	1.16	5
IC/TS	-0.79	5	7.36	4

The Value of the overall variables D^2 is 7.28

Table 8-13 Classifying the Aggregate Sample, Using IRR2AG

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	168	8	176
Failed	16	72	88
Error Rates	4.5%	18.1%	9.0%

8.4.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 8-14. At the assumed relative cost ratio from 1:1 to 40:1, with the IRR2AG aggregate model cost ratios of 10:1, the number of type I errors decreases from 47% to 20% while type II errors increases from 0% to 3%. Type I misclassification decreases when the cost ratio increases, and the type II misclassification increases when the cost ratio increases. Table 8-15 shows that the IRR2AG combined model is consistently less costly than proportional chance criterion ranging from 3.47 to 4.76 times.

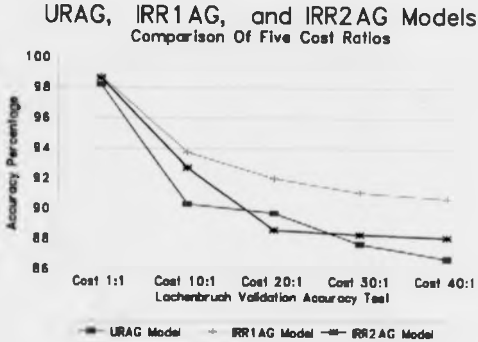
8-14 Model Efficiency Comparisons - Using IRR2AG Aggregate Sample.

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2AG Aggregate Model					
Non-failed	100	97	94	92	91
Failed	53	80	82	84	86
Overall Accuracy	98.6	93.0	89.6	88.3	88.7

8-15 Model Efficiency Comparisons - Using IRR2AG Aggregate Lachenbruch Validation Test

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2AG Aggregate Model					
Non-failed	176/176	171/176	163/176	162/176	161/176
Failed	46/88	69/88	72/88	74/88	75/88
Overall %	98.6	92.7	88.6	88.3	88.1
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{IRR2AG}	**0.014**	**0.092**	**0.18**	**0.22**	**0.25**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.14	3.47	3.38	4.09	4.76

Figure 8-1



8.5 Expansionary Phase - $_{UR}$B1 Model - Using Unadjusted Ratios

The URBI model's function based on the expansionary phase is:

Z_{URBI} = 20.24 + 1.32(FF/CL) + 2.06 (FF/TA)

The statistical significance of the computed function: The computed F-statistical for this URBI model is 60.46 while the tabulated value for F(2,42) = 8.18 for α = 0.001. The significance level of these two variables are greater than and equal 95%. Thus, the overall function indicate that the constructed URBI expansionary model possesses a highly significant discriminating power. FF/CL and FF/TA are two important variables. The within group correlation matrix based on the data of the expansionary phase are presented in Table 8-16. It shows that the highest correlation coefficients is (0.53) between FF/CL and FF/TA. The following are the results of the test.

8.5.1 Relative Contribution of Ratios

The relative contribution of the two ratios are given in Table 8-17. The most significant variable is the FF/CL. The ranking of the variables to the discriminant function is highly consistent.

8.5.2 Examining the Classification Accuracy Test

The difference in classificatory power between the results and proportional chance criterion of the URBI model in the expansionary phase is statistically significant. This has a normal distribution, the difference is 5.54, with 0.001 significance level. Table 8-18 displays the classification accuracy for the expansion phase. Table 8-18 shows that the model correctly classified 96% of the all the firms in the expansionary phase. Type II error is 3.3% (1 of 30) and Type I error is 6.7% (1 of 15). The overall error rate is also 4% for the expansion phase. The upward bias for the Lachenbruch validation sample bias test is identical to the original sample. (96% vs 96%), indicating that the results are not sensitive to sample bias.

Table 8-16 Within Groups Correlation Matrix - URBI Function

Var	FF/TA
FF/CL	0.53

Table 8-17 Relative Contribution Tests and Ranks of Financial Ratios in Expansionary Phase - URBI Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	3.07	1	76.95	1
FF/TA	1.64	2	23.05	2

The Value of the overall variables D2 is 12.38

Table 8-18 Classifying the Expansionary Period Sample, Using URBI

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	29	1	30
Failed	1	14	15
Error Rates	3.3%	6.7%	**4.4%**

8.5.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 8-19. At the assumed relative cost ratio from 1:1 to 40:1, with the URBI model cost ratios of 10:1, the number of type I errors keeps the same from 7% to 7% while type II errors also keeps the same from 3% to 3%. The URBI model is not **sensitive** to five different relative misclassification costs. The comparisons tests and their results as listed in Table 8-20. Table 8-20 shows that relative cost ratios for URBI model is consistently less costly than the URAG aggregate model except that of CI:CII = 1:1. URBI model is not significantly different from URAG aggregate model, but the percentage of correct classification of URBI is higher than URAG aggregate. Based on the Chi-square test, the null hypotheses H_4 can be rejected in certain specific cases.

Table 8-19 Model Efficiency Comparisons - Using URBI and URAG Aggregate Sample.

CI:CII	1:1	10:1	20:1	30:1	40:1
URBI Model					
Non-failed	97	97	97	97	97
Failed	80	93	93	93	93
Overall Accuracy	96.2	96.0	95.4	95.1	94.9
URAG Aggregate Model					
Overall Accuracy	98.8	90.7	90.0	88.0	88.5

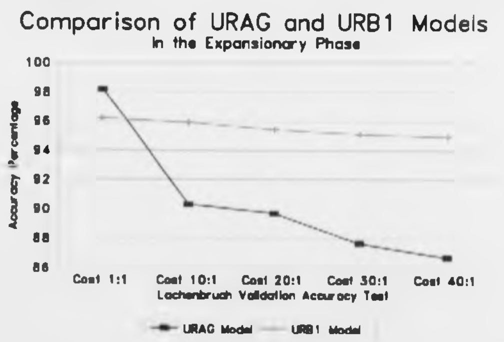
8-20 Model Efficiency Comparisons - Using URBI and URAG Aggregate Lachenbruch Validation Test

CI:CII	1:1	10:1	20:1	30:1	40:1
URBI Model					
Non-failed	29/30	29/30	29/30	29/30	29/30
Failed	12/15	14/15	14/15	14/15	14/15
Overall %	96.2	95.9	95.4	95.1	94.9
Cutoff Score	-3.47	-1.17	-0.48	-0.07	0.21
EC_{URBI}	**0.038**	**0.052**	**0.07**	**0.09**	**0.11**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	1.52	6.15	8.71	10.0	10.8
UR Aggregate Model					
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
URBI %	211	100	100	100	100
URAG Aggregate %	100	230	228	255	254
T Test					
T-Value	0.992	2.147b	1.633a	1.822b	2.147b
Significance	0.319	0.143	0.201	0.177	0.143

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$

c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

Figure 8-2



8.6 Expansionary Phase - IRR1B1 Model

A summary of the coefficients and other statistics based on 15 failed and 30 non-failed firms in the expansion period from years 1974 to year 1978 is presented as below. The results of the discriminant function statistics for the B1 model using industry mean ratios on the basis of the expansionary phase as follows:

$$Z_{IRR1B1} = 1.76 + 9.41(WC/TA) - 9.87(CA/TS) - 3.19(OP/TP) - 6.05(NI/NW).$$

The statistical significance of the computed function: The computed F-statistic for this function is 47.98 while the tabulated value for $F(4.40) = 5.70$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed IRR1B1 expansionary model possesses a highly significant discriminating power. All of the four variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 8-21. This Table shows that the highest correlation is (-0.29) between WC/TA and NI/NW.

8.6.1 Relative Contribution of Ratios

Table 8-22 presents the four measures of the variables' relative importance. The most important variable is the WC/TA.

8.6.2 Examining the Classification Accuracy Test - Using IRR1B1

The total sample of 45 firms in expansion phase is examined by using data from one statement prior to failure. The classification rates for the expansion period using the industry mean ratios (IRR1B1) is given in Table 8-23. The classificatory power of the expansion phase model using IRR1B1 is statistically significant compared to proportional chance model. The test statistical for the difference between the results and proportional chance is 6.08, with 0.001 significance level. Type I accuracy is

100% (15 of 15) and Type II accuracy is 100% (30 of 30). The overall accuracy is 100% (45 of 45).

Table 8-21 Within Groups Correlation Matrix - IRR1B1 Function

Var	CA/TS	OP/TP	NI/NW
WC/TA	0.25	-0.17	-0.29
CA/TS		0.03	0.22
OP/TP			-0.09

Table 8-22 Relative Contribution Tests and Ranks of Financial Ratios in the Expansion Phase - IRR1B1 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
WC/TA	5.36	1	50.63%	1
CA/TS	-4.04	2	11.85%	4
OP/TA	-3.12	4	14.18%	3
NI/NW	-3.20	3	23.33%	2

The Value of the overall variables D_2 is 20.63

Table 8-23 Classifying the Expansionary Sample, Using IRR1B1

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	30	0	30
Failed	0	15	15
Error Rates	0%	0%	0%

8.6.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five input misclassification costs is shown in Table 8-24 and 8-25. Relative cost ratios for IRR1BI are always lower than IRR1AG and URAG aggregate model. IRR1BI model are better than the proportional chance model with respect to the percentage of correct classifications. Overall, the Chi-square test yield significant evidence to reject the null hypotheses H_5 and H_6. Table 8-25 shows that the IRR1BI model performed better than that of IRR1AG and URAG models one year prior to failure.

Table 8-24 Model Efficiency Comparisons - Using IRR1BI, IRR1AG, and URAG Aggregate Model in the Expansion Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1BI Model					
Overall Accuracy	100	100	100	100	100
IRR1AG Aggregate Model					
Overall Accuracy	98.7	94.1	93.1	92.2	91.4
URAG Aggregate Model					
Overall Accuracy	98.8	90.7	90.0	88.0	88.5

Table 8-25 Model Efficiency Comparisons - Using IRR1B1, IRR1AG ,and URAG Aggregate Lachenbruch Validation Test

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1B1 Model					
Non-failed	30/30	30/30	30/30	30/30	30/30
Failed	14/15	15/15	15/15	15/15	15/15
Overall %	99.8	100	100	100	100
IRR1B1 Model					
EC_{IRR1B1}	**0.002**	**0.00**	**0.00**	**0.00**	**0.00**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	29	3.2	6.1	9.0	11.9
IRR1AG Aggregate Model					
EC_{IRR1AG}	**0.013**	**0.08**	**0.12**	**0.17**	**0.20**
UR Aggregate Model					
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR1B1 %	20.0	0.00	0.00	0.00	0.00
IRR1AG Aggregate	65	80	120	170	200
URAG Aggregate %	180	120	160	230	280
T Test*					
T-Value	3.56	3.841	3.645	3.841	4.037
Significance	0.059c	0.05d	0.056c	0.050d	0.045d
T Test**					
T-Value	5.165d	5.873d	5.206d	5.455d	5.873d
Significance	0.023	0.015	0.023	0.020	0.015

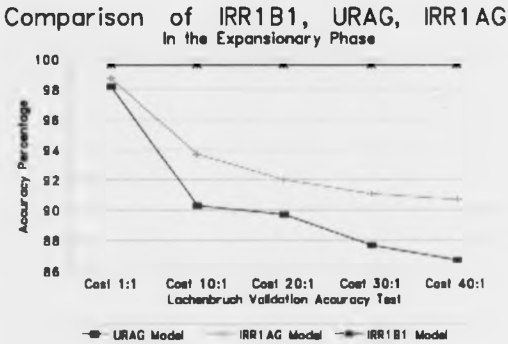
* T-Test Between IRR1BI and IRR1AG aggregate model.

** T-Test IRR1BI and URAG aggregate model.

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$,

c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

Figure 8-3



8.7 Model B1 - Using Industry Median Ratios (IRR2B1)

The IRR2B1 model's function based on the expansionary phase is:

$Z_{IRR2B1} = -11.89 + 8.56(FF/CL) - 1.29(OP/TP) + 8.02(TS/TA)$

The statistical significance of the computed function: The computed F-statistical for this model is 42.44 while the tabulated value for $F(3,41) = 6.55$ for $\alpha = 0.001$. The significance level of these three variables are greater than and equal 95%. Thus, the overall function indicate that the constructed IRR2B1 expansionary model possesses a highly significant discriminating power. FF/CL, OP/TP and TS/TA are three important variables. The within group correlation matrix based on the data of the expansionary phase are presented in Table 8-26. It shows that the highest correlation coefficients is (-0.44) between FF/CL and OP/TP. The following are the results of the test.

8.7.1 Relative Contribution of Ratios

The relative contribution of the three independent variables are presented in Table 8-27. The most important variable is the FF/CL.

8.7.2 The Classification Accuracy and Validation Test

The classificatory power of the IRR2B1 model is statistically significant different to proportional chance, at the 0.001 significance level. Table 8-28 presents the classification matrix for the expansion phase sample. Table 8-28 shows that the model correctly classified 96% of the all the firms in the expansionary phase. Type II error is 7% (2 of 30) and Type I error is 0% (0 of 15). The overall error rate is also 4% for the expansion phase. The upward bias in the IRR2B1 model appears to be slight since the Lachenbruch results are only two percent worse, indicating that the results are not all sensitive to sample bias.

Table 8-26 Groups Correlation Matrix - IRR2B1 Function

Var	OP/TP	TS/TA
FF/CL	-0.44	0.09
OP/TP		-0.05

Table 8-27 Relative Contribution Tests and Ranks of Financial Ratios in Expansionary Phase - IRR2B1 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	3.33	1	78.67	1
OP/TP	-1.58	2	16.50	2
TS/TA	1.21	3	4.82	3

The Value of the overall variables D^2 is 13.35

Table 8-28 Classifying the Expansionary Period Sample, Using IRR2B1

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	28	2	30
Failed	0	15	15
Error Rates	7%	0%	4%

8.7.3 Sensitivity to Prior Probabilities and Misclassification Costs

At the assumed relative cost ratio, use of the IRR2B1 model performed consistently better than that of IRR2AG and URAG combined models. The comparison between the measures of efficiency is made in Table 8-30. This Table shows that the IRR2B1 model outperformed IRR2AG and URAG models for various input assumption except that of cost ratios = 1:1. Overall, the chi-square test yield no significant evidence to reject the null hypotheses H_7 and H_8.

Table 8-29 Model Efficiency Comparisons - Using IRR2B1 ,IRR2AG and URAG Aggregate Sample in Expansion Phase Classification

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B1 Model					
Overall Accuracy %	96	96	96	97	97
IRR2AG Aggregate Model					
Overall Accuracy %	98.6	93.0	89.6	88.3	88.7
URAG Aggregate Model					
Overall Accuracy %	98.8	90.7	90.0	88.0	88.5

Table 8-30 Model Efficiency Comparisons - IRR2B1, IRR2AG, and URAG Aggregate Sample in the Expansion Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B1 Model					
Non-Failure	29/30	28/30	28/30	28/30	28/30
Failure	11/15	14/15	14/15	15/15	15/15
Overall %	96	93.4	93.4	96.6	97.0
EC IRR2B1	**0.04**	**0.084**	**0.06**	**0.064**	**0.064**
IRR2 Aggregate Model					
EC_{IRR2AG}	**0.014**	**0.092**	**0.18**	**0.22**	**0.25**
UR Aggregate Model					
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR2B1 %	285	100	100	100	100
IRR2AG %	100	109	300	343	390
URAG %	128	142	266	359	437
T-Test *					
T-Value	0.686	0.238	0.772	1.665c	1.665c
Significance	0.407	0.595	0.380	0.177	0.197
T-Test **					
T-Value	0.346	1.011	0.639	1.822c	2.147c
Significance	0.556	0.315	0.424	0.177	0.143

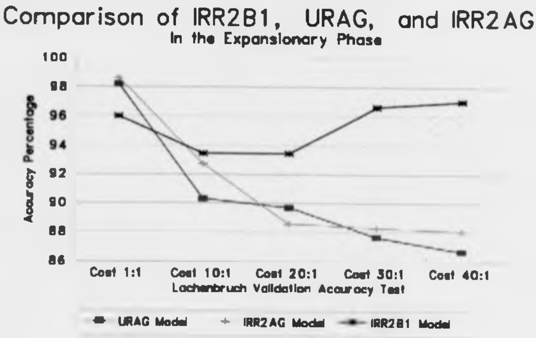
* T-Test between IRR2BI and IRR2AG aggregate model.

** T-Test between IRR2BI and URAG aggregate model.

c = Statistically different for $\alpha = 0.10$.

d = Statistically different for $\alpha = 0.05$

Figure 8-4



8-8 Recessionary Phase - Using Unadjusted Ratios (URB2)

The unadjusted ratios B2 model's function based upon 37 failed and 74 non-failed firms in the recession phase from years 1979 to year 1981 is presented below:

Z_{URB2} = 7.62 - 3.12(NI/TS) + 2.45(EBIT/TA) - 0.13(TL/TA) - 1.62(IC/TS).

The statistical significance of the computed function: The computed F-statistic for this function is 46.66 while the tabulated value for while the tabulated value for $F(4,106) = 5.04$ for $\alpha = 0.001$. Thus, this recession unadjusted ratios function possesses a highly significant discriminating power. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the unadjusted ratios from recessionary phase, in Table 8-31.

8.8.1 Relative Contribution of Ratios

The relative contribution of each ratio is shown in Table 8-32. The highest ranking in the unadjusted ratios recessionary phase is EBIT/TA. However, the value of the overall D^2 is 7.78.

8.8.2 Examining the Classification Accuracy Test

The classificatory power of the URB2 model is statistically significant different to the proportional chance criterion. The test statistic for the difference between the results and proportional chance is 7.87, with 0.001 significance level. Table 8-33 presents the classification rates for the recessionary sample. Table 8-33 shows that the model correctly classified 92% of all the firms in the combined sample. Type II error is 3% (7 of 37) and type I error is 19% (2 of 74). The result for the Lachenbruch validation sample bias test is identical to the original sample (92% vs 92%).

Table 8-31 Within groups Correlation Matrix - URB2 Model

Var	EBIT/TA	TL/TA	IC/TS
NI/TS	0.41	-0.17	-0.22
EBIT/TA		-0.49	-0.55
TL/TA			0.52

Table 8-32 Relative Contribution Tests and Ranks of Financial Ratios in Recessionary Phase - URB2 Model

Variables	Standardized Coefficients	Ranked	Mosteller's & Wallace's %	Ranked
NI/TS	-1.90	2	10.71%	3
EBIT/TA	1.96	1	38.83%	1
TL/TA	-1.66	3	37.80%	2
IC/TS	-1.05	4	10.64%	4

The Value of the overall variables D^2 is 7.78

Table 8-33 Classifying the Recessionary Phase Sample, Using URB2

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	72	2	74
Failed	7	30	37
Error Rates	3%	19%	8%

8.8.3 Sensitivity to Prior Probabilities and Misclassification Costs

Table 8-34 shows that the comparison is made between the URB2 and the URAG aggregate functions on each of the two model's and includes the two important measures of efficiency. Table 8-35 shows that the URB2 model marginally outperformed URAG aggregate model for the cost ratios ranging from 1:1 to 10:1. As regards the cost ratios ranging from 20:1 to 40:1, URAG aggregate model outperformed URB2 model. URB2 is not statistically different from URAG aggregate, but the percentage of correct classification is sometimes slightly higher than URAG aggregate. Based on the chi-square test, the null hypotheses H_0 cannot be rejected.

8-34 Model Efficiency Comparisons - Using URB2 and URAG Aggregate in the Recession Sample

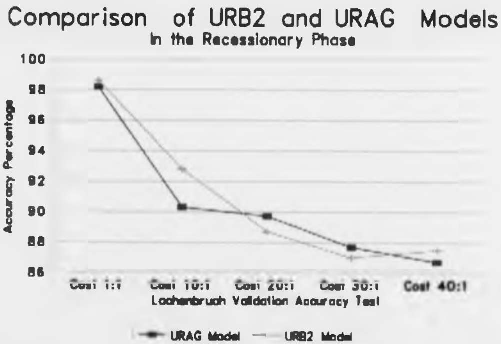
CI:CII	1:1	10:1	20:1	30:1	40:1
URB2 Model Overall Accuracy %	98.8	93.5	88.7	87.0	87.5
URAG Aggregate Model Overall Accuracy %	98.8	90.7	90.0	88.0	88.5

8-35 Model Efficiency Comparisons - Using URB2 and URAG Aggregate Lachenbruch Validation Test in the Recessionary Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
URB2 Model					
Non-failed	74/74	72/74	69/74	68/74	68/74
Failed	19/37	29/37	30/37	30/37	31/37
Overall %	98.6	92.8	88.7	87	87.5
EC_{URB2}	**0.014**	**0.09**	**0.17**	**0.27**	**0.29**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.14	3.55	3.58	3.33	4.10
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
URB2 %	100	100	106	117	103
URAG %	128	133	100	100	100
T Test *					
T-Value	0.204	0.60	0.007	0.042	0.067
Significance	0.651	0.439	0.935	0.839	0.798

* T-Test between URB2 and URAG aggregate model.

Figure 8-5



8-9 Recessionary Phase - Using Industry Mean Ratios (IRR1B2)

The industry mean ratios B2 model's function based upon the recessionary phase is:

$$Z_{IRR1B2} = 5.79 - 7.21(TD/TA) + 7.03(FF/TA) - 3.19(NI/TA) - 5.12(IC/TS) + 3.28(CA/TA)$$

The statistical significance of the computed function: The computed F-statistic for this function is 43.92 while the tabulated value for while the tabulated value for $F(5,105) = 4.46$ for $\alpha = 0.001$. Thus, this recession IRR1B2 function possesses a highly significant discriminating power. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the industry mean ratios from recessionary phase, in Table 8-36.

8.9.1 Relative Contribution of Ratios

The relative contribution of each ratio is shown in Table 8-37. TD/TA is the highest ranking in the recessionary phase. The variables are similarly ranked by two methods. However, the value of the overall D^2 is 9.24.

8.9.2 Examining the Classification Accuracy Test

The classificatory power of the IRR1B2 model is statistically significant different to the proportional chance criterion. The test statistic for the difference between the results and proportional chance is 8.51, with 0.001 significance level. Table 8-38 presents the classification rates for the recessionary sample. Table 8-38 shows that the model correctly classified 95% of all the firms in the recessionary sample. Type II error is 3% (2 of 74) and type I error is 11% (4 of 33). The result for the Lachenbruch validation sample bias test is one percent worse to the original sample (95% vs 94%).

Table 8-36 Within Groups Correlation Matrix - IRR1B2 Model

Ratios	FF/TA	NI/TA	IC/TS	CA/TA
TD/TA	-0.48	-0.03	0.57	0.24
FF/TA		0.11	-0.42	-0.17
NI/TA			-0.01	-0.15
IC/TS				-0.03

Table 8-37 Relative Contribution Tests and Ranks of Financial Ratios in Recessionary Period - IRR1B2 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
TD/TA	-1.94	1	38.36%	1
FF/TA	1.75	2	30.54%	2
NI/TA	-1.56	3	7.93%	4
IC/TS	-1.22	4	21.73	3
CA/TA	1.08	5	1.41	5

The Value of the overall variables D^2 is 9.24

Table 8-38 Classifying the Recessionary Period Sample, Using IRR1B1

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	72	2	74
Failed	4	33	37
Error Rates	3%	11%	5%

8.9.3 Sensitivity to Prior Probabilities and Misclassification Costs

The comparison between the IRR1B2 and the IRR1AG and URAG aggregate functions is made in Table 8-39 and Table 8-40. Table 8-40 shows that the IRR1B2 model outperformed IRR1AG and URAG aggregate model under the various input misclassification costs. The results are tested with the chi-square test for differences in probabilities, only two pair of comparison between IRR1B2 and URAG aggregate shows evidence of a statistical difference in classification accuracy (T = 3.529 and T = 1.656). However, this is not consistent. Based on these observations, the null hypotheses H_{10} and H_{11} cannot be rejected.

8-39 Model Efficiency Comparisons - Using IRR1B2, IRR1AG, and URAG Aggregate in the Recessionary Phase

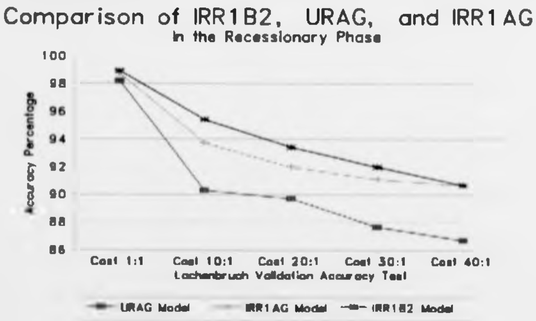
CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1B2 Model Overall Accuracy %	99	95.4	94.3	92.7	93.2
IRR1AG Aggregate Overall Accuracy %	98.7	94.1	93.1	92.2	91.4
URAG Aggregate Model Overall	98.8	90.7	90.0	88.0	88.5

8-40 Model Efficiency Comparisons - Using IRR1B2, IRR1AG and URAG Aggregate Lachenbruch Validation Test in the Recessionary Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1B2 Model					
Non-failed	74/74	72/74	71/74	70/74	68/74
Failed	23/37	33/37	33/37	33/37	33/37
Overall %	98.9	95.4	93.4	92	90.5
EC_{IRR1B2}	**0.004**	**0.04**	**0.10**	**0.15**	**0.20**
EC_{pmp}	0.058	0.32	0.61	0.90	1.19
Times	14.5	8.0	6.1	6.0	5.95
EC_{IRR1AG}	**0.013**	**0.08**	**0.12**	**0.17**	**0.20**
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR1B2 %	100	100	100	100	100
IRR1AG %	325	200	120	113	100
URAG %	450	300	160	153	140
T Test *					
T-Value	0.118	0.760	0.188	0.061	0.046
Significance	0.732	0.383	0.664	0.805	0.831
T Test **					
T-Value	0.208	3.529	1.656	1.254	0.600
Significance	0.649	**0.06c**	**0.198b**	0.263	0.439

* T-Test between IRR1B2 and IRR1AG aggregate model.
** T-Test between IRR1B2 and URAG aggregate model.
c = Statistically different for $\alpha = 0.10$, b = Statistically different for $\alpha = 0.20$

Figure 8-6



8-10 The Recessionary Phase - Using Industry Median Ratios

The IRR2B2 model's function based upon the recessionary sample is:

Z_{IRR2B2}=-7.42-7.26(TD/TA)-4.0(RE/TA)+8.45(EBIT/TA)-1.81(IC/TS)-0.87(OP/TP).

The statistical significance of the computed function: The computed F-statistic for this function is 57.51 while the tabulated value for while the tabulated value for $F(5,105) = 4.46$ for $\alpha = 0.001$. Thus, this IRR2B2 function possesses a highly significant discriminating power. Each variables contributed significantly to the model at least better than $\alpha = 0.05$. The relationship between the variables is presented by the within groups correlation matrix, based on the data of the IRR2B2 recessionary sample, in Table 8-41. The relationship between all the five variables with some different correlation coefficients. This Table shows that the highest correlation coefficients is (-0.48) between TD/TA and EBIT/TA.

8.10.1 Relative Contribution of Ratios

The relative contribution of each independent variable is shown in Table 8-42. The highest ranking by Mosteller and Wallace's measure is TD/TA. However, the value of the overall variables D^2 is 12.10 which achieved a higher rank than that of IRR1B2 function.

8.10.2 Examining the Classification Accuracy Test

The IRR2B2 recessionary model is significantly better than the proportional chance criterion. The test statistic for the difference between the results and proportional chance is 8.51. This has a normal distribution, with 0.001 significance level. Table 8-43 shows the classification matrices for the IRR2B2 recessionary samples. Table 8-43 shows that the model correctly classified 95% of all the firms in the recessionary sample. Type II error is 3% (2 of 74) and Type I error is 8% (3 of 37). The overall error rate is 5%. The result for the Lachenbruch validation sample bias test is two percent worse to the original sample (95% vs 93%), indicating that the results are not all sensitive to sample bias.

Table 8-41 Groups Correlation Matrix - IRR2B2 Function

Var	RE/TA	EBIT/TA	IC/TS	OP/TP
TD/TA	0.11	-0.48	0.24	0.35
RE/TA		0.17	0.15	0.04
EBIT/TA			-0.19	-0.41
IC/TS				0.26

Table 8-42 Relative Contribution Tests of Each Independent Variables - IRR2B2 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
TD/TA	-2.10	3	33.91	1
RE/TA	-2.60	1	19.04	3
EBIT/TA	2.19	2	26.06	2
IC/TS	1.32	4	11.27	4
OP/TP	0.99	5	9.69	5

The Value of the overall variables D^2 is 12.10

Table 8-43 Classifying the Recessionary Period Sample, Using IRR2B2

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	72	2	74
Failed	3	34	37
Error Rates	3%	8%	5%

8.10.3 Sensitivity to Prior Probabilities and Misclassification Costs

The comparison between the IRR2B2 and the IRR2AG aggregate functions is made in Table 8-44 and Table 8-45. Table 8-45 shows that the IRR2B2 model outperformed IRR2AG and URAG aggregate models under the various input misclassification costs except that of CI:CII = 1:1. The chi-square test shows that IRR2B2 is not significantly different IRR2AG and URAG aggregate models except that of CI:CII = 1:1. Therefore, H_{12} and H_{13} can be rejected in most specific instances.

8-44 Model Efficiency Comparisons - Using IRR2B2 IRR2AG and URAG Aggregate in the Recessionary Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B2 Model					
Overall Accuracy %	98.2	96	94.5	92.6	91.9
IRR2AG Aggregate					
Overall Accuracy %	98.6	93.0	89.6	88.3	88.7
URAG Aggregate Model					
Overall Accuracy %	98.8	90.7	90.0	88.0	88.5

8-45 Model Efficiency Comparisons - Using IRR2B2, IRR2AG and URAG Aggregate Lachenbruch Validation Test in the Recessionary Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B2 Model					
Non-failed	73/74	71/74	69/74	68/74	68/74
Failed	28/37	34/37	34/37	34/37	34/37
Overall %	98	95	92.8	91.9	91.9
EC_{IRR2B2}	**0.020**	**0.063**	**0.11**	**0.15**	**0.18**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	2.9	5.07	5.54	6.0	6.61
EC_{IRR2AG}	**0.014**	**0.092**	**0.18**	**0.22**	**0.25**
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR2B2 %	142	100	100	100	100
IRR2AG %	100	146	163	146	138
URAG %	128	193	145	153	155
T Test *					
T-Value	3.115c	1.442a	1.254	0.548	0.548
Significance	0.078	0.23	0.263	0.459	0.459
T Test**					
T-Value	2.030a	3.529c	0.999	0.710	1.083
Significance	0.154	0.060	0.318	0.399	0.298

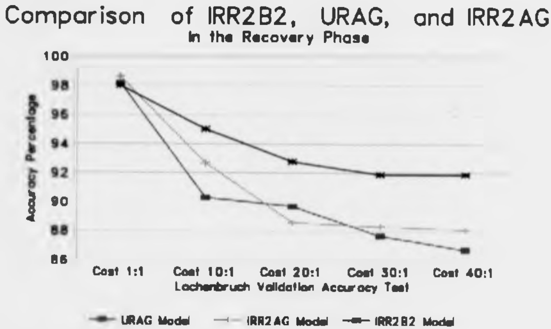
* T-Test between IRR2B2 and IRR2AG aggregate model.

** T-Test between IRR2B2 and URAG aggregate model.

a = Statistically different for $\alpha = 0.25$, b = Statistically different for $\alpha = 0.20$

c = Statistically different for $\alpha = 0.10$.

Figure 8-7



8.11. The Recovery Phase - Using Unadjusted Ratios (URB3)

36 failed and 72 non-failed firms in the recovery phase from years 1982 to year 1985 is included as follow. The URB3 model's function based on the recovery phase is:

$$Z_{URB3} = 5.34 - 0.17(TD/TA) + 0.52(FF/CL) - 2.56(NI/TS) + 1.49(TS/NPA) + 2.86Log(TA)$$

The statistical significance of the computed function: The computed F-statistical for this URB3 model is 38.96 while the tabulated value for $F(5,102) = 4.47$ for $\alpha = 0.001$. The significance level of these five variables are greater than and equal 95%. Thus, the overall function indicate that the constructed URB3 recovery model possesses a highly significant discriminating power. The within group correlation matrix based on the data of the recovery phase are shown in Table 8-46. It shows that the highest correlation coefficients is (0.54) between NI/TS and FF/CL. The following are the results of the test.

8.11.1 Relative Contribution of Ratios

The relative contribution of the five ratios are given in Table 8-47. The most significant variable is the TD/TA and FF/CL. The first three ranking of the variables to the discriminant function is highly consistent.

8.11.2 Classification Accuracy and Validation Test

The classificatory power of the URB3 model in the recovery phase is statistically significant difference between the results and proportional chance criterion. This has a normal distribution, the difference is 8.08, with 0.001 significance level. Table 8-48 displays the classification accuracy for the recovery phase. Table 8-48 shows that the model correctly classified 93% of the all the firms in the recovery phase. Type II error is 4% (3 of 72) and Type I error is 14% (5 of 36). The overall error rate is also 7% for the recovery phase. The upward bias for the Lachenbruch validation sample bias test is exactly identical to the original sample, (93% vs 93%), indicating that the results are not sensitive to sample bias.

Table 8-46 Groups Correlation Matrix - URB3 Function

Var	FF/CL	NI/TS	TS/NPA	Log(TA)
TD/TA	-0.35	-0.40	0.38	0.32
FF/CL		0.54	-0.32	0.11
NI/TS			-0.28	-0.09
TS/NPA				0.06

Table 8-47 Relative Contribution Tests and Ranks of Financial Ratios in Recovery Phase - URB3 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
TD/TA	-2.58	1	48.51	1
FF/CL	1.65	2	30.55	2
NI/TS	-1.45	3	9.98	3
TS/NPA	1.29	4	3.83	5
Log(TA)	1.08	5	7.13	4

The Value of the overall variables D^2 is 8.43

Table 8-48 Classifying the Recovery Phase Sample, Using URB3

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	69	3	72
Failed	5	31	36
Error Rates	4%	14%	7%

8.11.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons is shown in Table 8-49 and Table 8-50. The Table 8-50 shows that relative costs for URB3 model are consistently less costly than the URAG aggregate model. However, based upon the chi-square test, the null hypotheses H_{14} cannot be rejected.

Table 8-49 Model Efficiency Comparisons - Using URB3 and URAG Aggregate Sample.

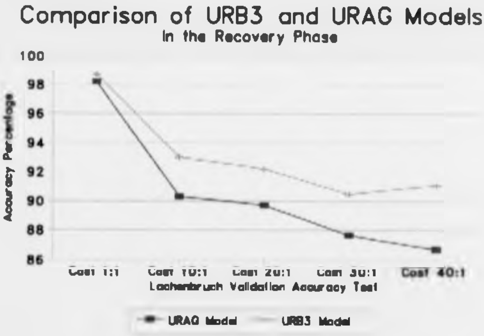
CI:CII	1:1	10:1	20:1	30:1	40:1
URB3 Model					
Overall Accuracy %	98.8	95.0	92.2	93.9	94.8
URAG Aggregate Model					
Overall Accuracy %	98.8	90.7	90.0	88.0	88.5

8-50 Model Efficiency Comparisons - Using URB3 and URAG Aggregate Lachenbruch Validation Test in the Recovery Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
URB3 Model					
Non-failed	72/72	69/72	69/72	68/72	65/72
Failed	20/36	30/36	31/36	31/36	33/36
Overall %	98.7	93.0	92.2	90.5	91.1
EC_{URB3}	0.013	[illegible]	0.10	0.18	0.19
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.46	3.55	6.10	5.0	6.26
UR Aggregate Model					
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
URB3 %	100	100	100	100	100
URAG %	138	133	160	127	147
T Test *					
T-Value	0.011	0.928	0.859	0.588	0.482
Significance	0.916	0.335	0.354	0.443	0.488

* T-Test between URB3 and URAG aggregate model.

Figure 8-8



8.12 Recovery Phase - IRR1B3 Model

36 failed and 72 non-failed firms in the recovery phase from years 1982 to year 1985 is included as follow. The results of the discriminant function statistics using industry mean ratios on the basis of the recovery phase as follows:

$$Z_{IRR1B3} = -4.25-2.31(NI/NW)+4.65(FF/CL)-4.88(IC/TS)-1.10(OP/TA)-1.70(CA/TA)$$

The statistical significance of the computed function: The computed F-statistic for this function is 41.20 while the tabulated value for $F(5,102) = 4.46$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed IRR1B3 recovery model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 8-51. This table shows that the highest correlation is (0.33) between NI/NW and FF/CL.

8.12.1 Relative Contribution of Ratios

Table 8-52 presents the measures of the five variables' relative importance. The most important variable is the NI/NW. The ranking across these two tests are very consistent. The value of overall D^2 is 8.92.

8.12.2 Examining the Classification Accuracy

The total sample of 108 firms in the recovery phase is examined. The classification rates for the recovery period using the industry mean ratios is given in Table 8-53. The classificatory power of the recovery phase model using IRR1B3 is statistically significant compared to proportional chance model. The test statistical for the difference between the results and proportional chance is 8.72, with 0.001 significance level. Type II error is 0% (0 of 72) and Type I error is 11% (4 of 36). The overall accuracy is 96%. The upward bias for the Lachenbruch validation sample bias test is one percent worse to the original sample. (96% vs 95%), indicating that the results are not sensitive to sample bias.

Table 8-51 Within Groups Correlation Matrix - IRR1B3 Function

Var	FF/CL	IC/TS	OP/TA	CA/TA
NI/NW	0.33	0.11	0.06	0.08
FF/CL		-0.15	-0.04	-0.32
IC/TS			0.12	0.24
OP/TA				-0.15

Table 8-52 Relative Contribution Tests and Ranks of Financial Ratios in the Recovery Phase - IRR1B3 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
NI/NW	-1.68	1	32.23	1
FF/CL	1.67	2	31.68	2
IC/TS	-1.26	3	21.45	3
OP/TA	-0.92	4	13.31	4
CA/TA	0.68	5	1.32	5

The Value of the overall variables D^2 is 8.92

Table 8-53 Classifying the Recovery Phase, Using IRR1B3

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	72	0	72
Failed	4	32	36
Error Rates	0%	11%	4.4%

8.12.3 Sensitivity to Prior Probabilities and Misclassification Costs

The comparison between the measures of efficiency is shown in Table 8-54 and Table 8-55. Table 8-55 shows that relative costs for IRR1B3 are always lower than IRR1AG and URAG aggregate model. IRR1B3 is not significantly different from IRR1AG aggregate model based on chi-square test. The null hypotheses H15 cannot be rejected. The chi-square test gives evidence to reject the null hypotheses H16, but the results are not consistent. It appears that the null hypotheses H16 can be rejected only in some specific instances. However, IRR1B3 model performed better than that of IRR1AG and URAG aggregate model with respect to the percentage of correct classifications.

Table 8-54 Model Efficiency Comparisons - Using IRR1B3, IRR1AG ,and URAG Aggregate Model in the Recovery Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1B3 Model					
Overall Accuracy %	99	95.4	94.1	93.3	92.7
IRR1AG(Aggregate)	98.7	94.1	93.1	92.2	91.4
URAG (Aggregate)	98.8	90.7	90.0	88.0	88.5

8-55 Model Efficiency Comparisons - Using IRR1B3, IRR1 and UR Aggregate Lachenbruch Validation Test in the Recovery Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR1B3 Model					
Non-failed	72/72	72/72	70/72	70/72	70/72
Failed	23/36	28/36	32/36	32/36	32/36
Overall %	99	94.7	94.1	93.3	92.7
IRR1B3 Model					
EC_{IRR1B3}	**0.01**	**0.03**	**0.09**	**0.12**	**0.16**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	58	10.6	6.7	7.5	7.43
EC_{IRR1AG}	**0.013**	**0.08**	**0.12**	**0.17**	**0.20**
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR1B1 %	100	100	100	100	100
IRR1AG %	130	266	133	141	125
URAG %	180	400	177	191	175
T Test *					
T-Value	0.034	0.032	0.481	0.655	0.850
Significance	0.854	0.858	0.488	0.418	0.357
T Test **					
T-Value	0.360	1.535	2.296	2.651	3.275
Significance	0.549	**0.215a**	**0.130b**	**0.10c**	**0.070c**

* T-Test between IRR1B3 and IRR1AG aggregate model.

** T-Test between IRR1B3 and URAG aggregate model.

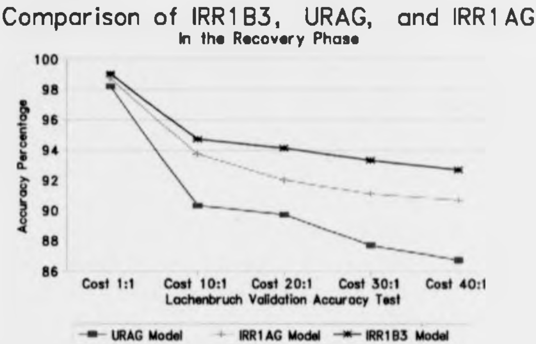
a = Statistically different for $\alpha = 0.25$,

b = Statistically different for $\alpha = 0.20$

c = Statistically different for $\alpha = 0.10$,

d = Statistically different for $\alpha = 0.05$

Figure 8-9



8.13 Recovery Phase - Using Industry Median Ratios (IRR2B3)

The IRR2B3 model's function based on 36 failed and 72 non-failed firms in the recovery phase is:

Z_{IRR2B3} = -0.27 + 2.78(FF/CL) -2.11(NI/TS) +0.46(Log(TA) +1.81(TS/TA) -0.94(OP/TP)

The statistical significance of the computed function: The computed F-statistical for this model is 27.29 while the tabulated value for $F(5,102) = 4.46$ for $\alpha = 0.001$. The significance level of these five variables are greater than and equal 95%. Thus, the overall function indicate that the constructed IRR2B3 recovery model possesses a highly significant discriminating power. FF/CL, NI/TS, Log(TA), TS/TA and OP/TP are all significant at the 0.05 or better. The within group correlation matrix based on the data of the recovery phase are presented in Table 8-56. It shows that the highest correlation coefficients is (-0.39) between FF/CL and OP/TP. The following are the results of the test.

8.13.1 Relative Contribution of Ratios

Table 8-57 shows that the most important variable is the FF/CL. The variables ranking across these two tests are quite consistent. The value of overall variables D^2 is 5.90.

8.13.2 The Classification Accuracy and Validation Test

The classification rates for the recovery phase using the industry median ratios is given in Table 8-58. The classificatory power of the recovery phase model using IRR2B3 is statistically significant compared to proportional chance model. The test statistical for the difference between the results and proportional chance is 7.23, with 0.001 significance level. Type II error is 6% (4 of 72) and Type I error is 22% (8 of 36). The overall accuracy is 89%. The upward bias for the Lachenbruch validation sample bias test is one percent worse to the original sample. (89% vs 88%), indicating that the results are not sensitive to sample bias.

Table 8-56 Groups Correlation Matrix - IRR2B3 Function

Var	NI/TS	Log(TA)	TS/TA	OP/TP
FF/CL	-0.14	0.13	0.08	-0.39
NI/TS		-0.02	0.39	0.23
Log(TA)			0.07	-0.07
TS/TA				-0.22

Table 8-57 Relative Contribution Tests and Ranks of Financial Ratios in Recovery Phase - IRR2B3 Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	1.86	1	59.24	1
NI/TS	-1.20	2	18.64	2
Log(TA)	0.46	4	2.85	4
TS/TA	0.39	5	2.70	5
OP/TP	0.91	3	16.54	3

The Value of the overall variables D^2 is 5.90

Table 8-58 Classifying the Recovery Phase Sample, IRR2B3 Model

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	68	4	72
Failed	8	28	36
Error Rates	6%	22%	11%

8.13.3 Sensitivity to Prior Probabilities and Misclassification Costs

Relative costs for IRR2B3 are not lower than IRR2AG and URAG aggregate model. IRR2B3 model perform nearly the similar results as those of IRR2AG and URAG aggregate model. Type II error increases when the cost ratios increases. Type II error for IRR2B3 model is not sensitive to the cost ratios and/or the prior probability when compared to Type I error given in Table 8-59. Table 8-60 shows the result of testing H_{17} and H_{18}. IRR2B3 is not statistically different from both IRR2AG and URAG aggregate models. Based on chi-square test, the null hypotheses H_{17} and H_{18} can not be rejected.

Table 8-59 Model Efficiency Comparisons - Using IRR2B3, IRR2AG and URAG Aggregate Model in Recovery Phase Classification

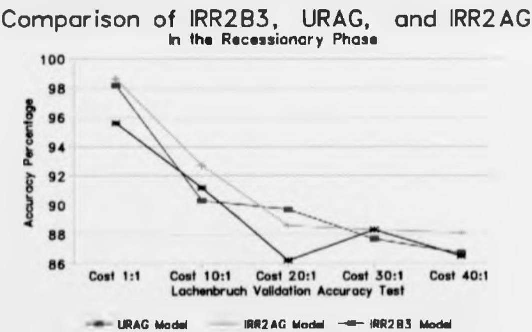
CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B3 Model Overall Accuracy %	97	93.3	88.2	89.8	88
IRR2AG (Aggregate)	98.6	93.0	89.6	88.3	88.7
URAG (Aggregate)	98.8	90.7	90.0	88.0	88.5

Table 8-60 Model Efficiency Comparisons - IRR2B3, IRR2, and UR Aggregate Model in the Recovery Phase

CI:CII	1:1	10:1	20:1	30:1	40:1
IRR2B3 Model					
Non-Failure	70/72	68/72	67/72	65/72	65/72
Failure	15/36	29/36	27/36	31/36	30/36
Overall %	95.6	91.2	86.2	88.3	86.5
EC_{IRR2B3}	**0.04**	**0.094**	**0.21**	**0.219**	**0.29**
ECprop	0.058	0.32	0.61	0.90	1.19
Times	1.45	3.4	2.90	4.10	4.10
EC_{IRR2AG}	**0.014**	**0.092**	**0.18**	**0.22**	**0.25**
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
IRR2B3 %	285	102	131	100	116
IRR2AG %	100	100	112	100	100
URAG %	128	130	100	104	112
T Test *					
T-Value	0.912	0.108	0.293	0.02	0.160
Significance	0.340	0.743	0.588	0.887	0.689
T Test **					
T-Value	0.360	0.186	0.457	0.001	0.006
Significance	0.549	0.667	0.499	0.972	0.936

* T-Test between IRR2B3 and IRR2AG aggregate model.
** T-Test between IRR2B3 and URAG aggregate model.

Figure 8-10



8.14 Summary and Conclusions

This has been an inevitably complex investigation comparing 3 different ratio forms (UR, IRR1, and IRR2) across 4 different time periods (AG, B1, B2, and B3) also exploring the sensitivity of the resulting 12 models to variation in priors and misclassification costs. Unlike chapter 7 where the classificatory accuracy being studied was between development and hold-out samples (ex post / ex ante), when stratifying the study by time period, the sample sizes precluded using a hold-out strategy. Instead we must rely on the Lachenbruch methodology for model validation.

Table 8-61 distils the essential findings of this part of the investigation. What we observe from Table 8-61 is that the classificatory accuracy of models based on industry mean ratios dominate the other both across the whole time period aggregated and for all the sub-time periods. The model forms : in terms of important parameters, and coefficients alters as the time periods alter. However, a constant finding is the superior classificatory ability of models developed using the industry relative (mean) ratios.

Table 8-61 Percentage Error Model

Time	UR	IRR1	IRR2
Aggregate 1974-1985	9.4%	6.8%*	9%
B1 Expansionary 1974-1978	4.4	0.0%*	4.4%
B2 Recessionary 1979-1981	8%	5.0%*	5%*
B3 Recovery 1982-1985	7%	4.4%*	11%

* is row minimum
IRR1 (industry mean) based models produce small percentage error rates across the sample time periods.

This finding added to the results of chapter 7 is additional evidential support in favour of analysts in this field working with the industry relative ratio form.

The qualification to these findings are:

1. Statistical significance ?

2. Stable for all costs and priors ?

3. Validation is only by Lachenbruch not by hold-out ?

It is hugely difficult for analysts to develop separate bankruptcy prediction models for different periods of the economic cycle. Not only there are fewer observations on which to develop a model, but there are problems in testing and use. In particular, an analyst has to forecast when the business cycle changes in order to decide which model to use. Can a model developed in the recovery phase be tested or applied in the expansionary phase of the cycle?

The results we have presented so far on the merits of the IRR1 form are then of theoretical importance, rather than of consequence to application. There are implications for practise since the results do illustrate the extent that costs are incurred by using a model developed without regard to the stage of the business cycle.

Summarised in Table 8-62 are the expected costs for all the models we have developed. The least cost model at every cost ratio CI:CII and for every time period uses the IRR1 ratio form (except for one anomalous result in period B2 when a cost ratio of 40:1 gives IRR2 as the least cost ratio form). For ease of comparison these least cost models are summarised in Table 8-63.

Table 6-62 Summary of Expected Costs

CI:CII	1:1	10:1	20:1	30:1	40:1
Expected Table Costs Source					
EC_{URAG} (8-5)	0.018	0.12	0.16	0.23	0.28
EC_{IRR1AG} (8-10)	0.013*	0.080*	0.12*	0.17*	0.20*
EC_{IRR2AG} (8-15)	0.014	0.092	0.18	0.22	0.25
EC_{URB1} (8-20)	0.038	0.052	0.07	0.09	0.11
EC_{IRR1B1} (8-25)	0.002*	0.000*	0.00*	0.00*	0.00*
EC_{IRR2B1} (8-30)	0.040	0.084	0.06	0.064	0.064
EC_{URB2} (8-35)	0.014	0.090	0.17	0.27	0.29
EC_{IRR1B2} (8-40)	0.004*	0.040*	0.10*	0.15*	0.20
EC_{IRR2B2} (8-45)	0.020	0.063	0.11	0.15*	0.18*
EC_{URB3} (8-50)	0.013	0.090	0.10	0.18	0.19
EC_{IRR1B3} (8-55)	0.010*	0.030*	0.09*	0.12*	0.16*
EC_{IRR2B3} (8-60)	0.040	0.094	0.21	0.21	0.29

* = Least expected cost in each sub-period of time
Conclusion IRR1 dominates except for period B2 cost ratios 40:1

Table 8-63 Expected Costs For Optimal Model (IRR1 Form)

CI:CII	1:1	10:1	20:1	30:1	40:1
Aggregate	0.013*	0.080*	0.12*	0.17*	0.20*
Expansionary	0.002*	0.000*	0.00*	0.00*	0.00*
Recessionary	0.004*	0.040*	0.10*	0.15*	0.20
Recovery	0.010*	0.030*	0.09*	0.12*	0.16*

Conclusion: For cost ratios CI:CII in excess of 20:1 cost advantage of developing separate models for separate parts of the business cycle evaporate. These results offer some comfort to the practical analyst in using an aggregate model rather than models developed for stages of the business cycle. When the cost ratios is high (toward realistic levels), there would be only a very small expected cost advantage in using business cycle models, if they could be developed. This is an important finding. As for as the use of the industry relative ratios form (IRR1) this chapter presents additional evidence in its favour, however, we have also conducted that the value of this evidence may not be large in a practical context.

Chapter 9 Empirical Results of Industry-Specific Difference

9.1 Introduction

Because of the effect of multi-period and industry differences, the instability of accounting ratios may impair failure prediction. A industry-specific model, the use of industry relative ratios, and controlling for business cycle characteristics are three methods to cope with instability. This section empirically tests hypothesis 19-24: are there no differences in the predictive ability of financial ratios, macro-economic and year dummy variables between the industry-specific models and between a model using unadjusted ratios. We grouped observations across industry into five groups. Contracting, General-Engineering, Textiles, Other Manufacturing, and Miscellaneous (see Chapter 5) to develop the industry-specific models (see discussion in sub-chapter 4-6). Evidence from this may provide useful insights in formulating government public policy and assisting private investment advisers by enhancing failure prediction rates. For example, firms in the Contracting group may fail for different financial reasons from those in the Textile industry. Thus if different industries have different financial characteristics, different financial variables may predict impending failure. However, the sample of observations used in each industry is more restricted than for the aggregate sample. The purpose of this chapter is to assess industry differences for each industry-specific model and the UR aggregate model. 41 **raw financial ratios**, four macro-economic variables, and 11 years dummy variables (as defined in chapter 6) used to develop industry-specific models and an aggregate model.

The aim is to analyse the importance of sectoral classification for the development of predictive discriminant models. The relative importance of each independent variable for five models can be measured by the standardized coefficients and Mosteller and Wallace's methods which are discussed in chapter 5 and used in chapter 7 and chapter 8. Due to the limited sample size to develop industry-specific models that could not allow a split-sample technique, and as before the Lachenbruch validation technique was employed. However, in order to test the hypotheses H_{22}, both split-sample and Lachenbruch validation techniques in classifying and predicting textile industry are used (see chapter 5). Results for each of three year's prior to failure for five broad industrial sectors are shown as below.

9.2 The Aggregate Model - Using Unadjusted Ratios (URAG)

The model was originally developed in the chapter 8.2. Crucial statistics about this model are: 88 failed and 176 non-failed firms were used to develop the aggregate model. The classificatory power of the UR aggregate model is statistically significant different to the proportional chance criterion. The aggregate unadjusted ratios function possesses a highly significant discriminating power. Type I error is 18.1% and Type II error is 5.1%. The overall accuracy is 91%. The Lachenbruch validation sample bias test is only one percent worse to the original sample (see: chapter 8.2).

9.3 Classification Accuracy - Industry-Specific Models

The entire sample is classified into five broad industrial sectors, Contracting, General-engineering, Textile, Other manufacturing and Miscellaneous industries. The number of firms in each sector is shown in section 5-2. A discriminant analysis and Lachenbruch validation technique are performed on each sector.

9.4 Contracting Sector

The model was developed upon the basis of the data of the one year prior to failure. The purpose is to compare the predictive ability of contracting industry model with the aggregate model. From the original list of variables, four financial variables were selected based on stepwise discriminant analysis. A summary of the coefficients and statistics on the basis of 11 failed and 22 non-failed companies in the contracting industry sample is as follows:

$$Z = 10.48 + 4.27(FF/CL) - 31.99(NI/TA) - 11.60(OP/TA) + 39.46(CA/TA)$$

The statistical significance of the computed function: The computed F-statistic for this function is 94.01 while the tabulated value for $F(4,28) = 6.25$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the Contracting industry model possesses a highly significant discriminating power. All of the variables were highly significant at levels better than 0.05 percent. The significance test therefore rejects the null hypotheses that the observations come from the same population. The within groups correlation which is shown in Table 9-1. This Table shows that the highest correlation is (-0.31) between FF/CL and OP/TP.

9.4.1 Relative Contribution of Ratios

In Table 9-2, we see that FF/CL is ranked highest in relative contribution according to standardised coefficient and Mosteller & Wallace's methods. It is therefore seen that FF/CL has contributed the most of the four variables. Unfortunately, the year dummies and macro-economic variables did not contribute to the contracting industry.

9.4.2 Examining the Classification Accuracy

Table 9-3 shows that the discriminant analysis of the contracting group displayed a very successful classification level in the model for a very superior classification for the first year prior to failure. The type I error is 0% and Type II error is 0% as well. The overall accuracy is 100%. In comparison with the aggregate model, the percentage of accuracy of the contracting sector is higher than that of aggregate model (100% vs 91%). It is obvious that year one prior to failure in the contracting industry has quite high predictive accuracy as compared with the aggregate model.

Table 9-1 Within Groups Correlation Matrix - Contracting Model

Var	NI/TA	OP/TP	CA/TA
FF/CL	-0.13	-0.31	-0.27
NI/TA		-0.26	0.11
OP/TP			-0.07

Table 9-2 Relative Contribution Tests of Each Independent Variables - Contracting Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	11.65	1	44.86	1
NI/TA	-14.39	2	30.19	2
OP/TP	-11.36	3	23.54	3
CA/TA	7.10	4	1.38	4

The Value of the overall variables D2 is 56.77

Table 9-3 Classifying the Contracting Sample, Using UR

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	22	0	22
Failed	0	11	11
Error Rates	0%	0%	0%

9.4.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of contracting model efficiency comparisons under five various input misclassification costs is shown in Table 9-4 and Table 9-5. Table 9-5 shows that the costs ratios from 1:1 to 40:1 performed better than that of the aggregate model one year prior to failure. Relative costs from contracting sector are always lower than aggregate model. The chi-square test gives evidence to reject the null hypotheses H19. There is a statistically significant difference between contracting sector and aggregate models.

Table 9-4 Model Efficiency Comparisons - Contracting Industry and Aggregate Classification

CI:CII	1:1	10:1	20:1	30:1	40:1
Contracting					
Overall Accuracy %	100	100	100	100	100
UR Aggregate %	98.8	90.7	90.0	88.0	88.5

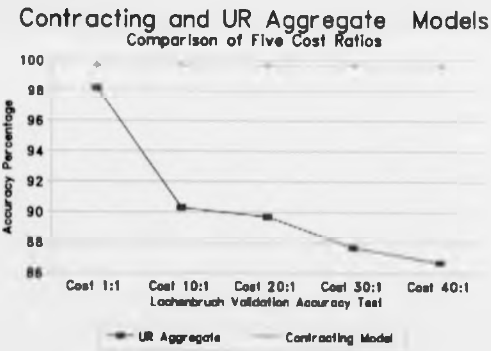
Table 9-5 Model Efficiency Comparisons - Contracting and Aggregate Model Lachenbruch Validation

CI:CII	1:1	10:1	20:1	30:1	40:1
Non-failed %	100	100	100	100	100
Failed %	100	100	100	100	100
Overall %	100	100	100	100	100
Contracting model					
$EC_{contracting}$	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
EC_{URAG}	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
Contracting Model %	0.00	0.00	0.00	0.00	0.00
UR Aggregate %	18	120	160	230	280
T-Test *					
T-Value	5.447d	4.327d	3.833d	4.017d	4.327d
Significance	0.020	0.038	0.050	0.045	0.038

* T-Test Comparison Between Contracting industry and UR aggregate model.

d = Statistically different for $\alpha = 0.05$

Figure 9-1



9.5 General-Engineering Group

Five variables are selected as the general-engineering sector model. The function, based upon the 9 failed and 18 non-failed firms, is presented and evaluated as follows:

$$Z = -39.39 - 1.44(CG) - 16.67(YR11) - 3.02(RE/TA) - 3.49(YR5)$$

The significant variables include CG(capital gearing), 1980 and 1984 Year dummies and RE/TA. The statistical significance of the computed function: The computed F-statistic for this function is 32.93 while the tabulated value for $F(4,22) = 6.81$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed general-engineering model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 9-6. This Table shows that the highest correlation is (-0.39) between CG and YR11.

9.5.1 Contribution of Ratios

YR5 and YR11 are an year dummy variables, which have the values of 1 for year 1980 (recessionary phase) and year 1984 (recovery phase) and 0 otherwise. The inclusion of these two variables indicate that the Z-score of textile companies, failed and non-failed, are probably affected by the recession and recovery economic conditions. However, it is interesting to note that the YR5 and YR11 year dummy variables entered the model with a 5% sig. level, while the univariate F test is insignificant with 5% sig. level. Nevertheless, if we remove this two dummy variables from the model, the Mahalanobis D^2 drop slightly a little, the model are still significant at the 0.001 level. The classification accuracy remains at 100%. Therefore, we conclude that the 1980 and 1984 year dummies can somewhat contribute marginally to this model as compared with other two financial ratios.

9.5.2 Examining the Classification Accuracy

The classificatory power of the General-Engineering model is statistically significant compared to the proportional chance criterion. In this comparison, the Z value is 4.73 for the proportional chance model, at the 0.001 significance level. The overall firms in the general-engineering industry provided satisfactory predictive accuracy for the first year prior to failure. Table 9-8 shows the percentage of correct classifications. It appears that the explanatory power of the General-Engineering model is quite stable.

Table 9-6 Groups Correlation Matrix - General-Engineering Model

Variable	YR11	RE/TA	YR5
CG	-0.39	0.36	0.16
YR11		-0.22	0.25
RE/TA			0.40

Table 9-7 Relative Contribution Tests of Each Independent Variables - General-Engineering Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
CG	-7.40	1	85.21	1
YR11	-5.33	2	1.00	3
RE/TA	-1.93	3	13.0	2
YR5	1.67	4	1.00	4

The Value of the overall variables D^2 is 24.94

Table 9-8 Classifying the Engineering-General

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	18	0	22
Failed	0	9	9
Error Rates	0%	0%	0%

9.5.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each General-Engineering model efficiency comparisons under five various input misclassification costs is shown in Table 9-9 and Table 9-10. Relative costs for General-Engineering model are always lower than the aggregate model. General-Engineering is statistically different from the aggregate model based on the chi-square test. Therfore, the results of this comparison reject the null hypotheses H_{20} above. Table 9-10 shows that the General-Engineering model performed better than that of the aggregate model.

Table 9-9 Model Efficiency Comparisons - General-Engineering Industry and UR Aggregate Model Classification

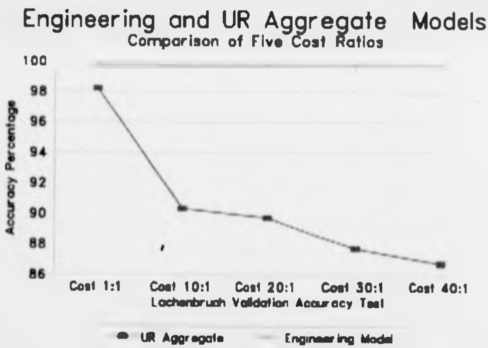
CI:CII	1:1	10:1	20:1	30:1	40:1
General Engineering Model					
Overall Accuracy %	100	100	100	100	100
URAG Aggregate %	98.8	90.7	90.0	88.0	88.5

Table 9-10 Model Efficiency Comparisons - General-Engineering Industry and UR Aggregate Model Lachenbruch Hold-Out Validation

CI:CII	1:1	10:1	20:1	30:1	40:1
Non-failed %	100	100	100	100	100
Failed %	100	100	100	100	100
Overall %	100	100	100	100	100
General-Engineering Model					
$EC_{engineering}$	**0.00**	**0.00**	**0.00**	**0.00**	**.00**
EC_{prop}	0.058	0.32	0.61	0.90	.19
EC_{UR} Aggregate	**0.018**	**0.12**	**0.16**	**0.23**	**.28**
Relative Cost Ratios					
General-Eng. %	0.00	0.00	0.00	0.00	0.00
UR Aggregate %	18	120	160	230	80
T-Test					
T-Value	5.122d	4.068d	3.603c	3.777c	4.068d
Significance	0.024	0.044	0.058	0.052	0.044

c = Statistically different for $\alpha = 0.10$, d = Statistically different for $\alpha = 0.05$

Figure 9-2



9.6 Textile Sector

Textiles are the only single homogeneous sector which included flooring covering, clothing, cotton & synthetic, wool and misc. textiles companies, to have sufficient firms (23 failed and 46 non-failed firms) to explore the empirical result using the split sample technique. Platt and Platt [1990] state that focusing on one industry is analogous to using industry relative ratios in samples including several industries since the relative positions of firms within the industry is reflected by the relative position on any given financial ratio. The textile sector sample size, in this study, is large enough to distinguish between ex post and ex ante sample so as to examine the stability of forecasting model in single industry compared with the industry relative ratios model. Accordingly, firstly, we develop the textile sector model and compared its results with the aggregate model. Secondly, we explore the stability of forecasting model in single textile industry as compared to IRR1 model.

The textile model, developed upon the basis of the 23 failed and 46 non-failed firms, was presented as follows:

$$Z = 0.54 + 0.85(FF/CL) - 0.12(TL/TA) - 1.88(NI/TS)$$

The statistical significance of the computed function: The computed F-statistic for this function is 36.93 while the tabulated value for $F(3,65) = 6.13$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed textile model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 9-11. This Table shows that the highest correlation is (-0.48) between FF/CL and TL/TA.

9.6.1 Relative Contribution of Ratios

The most important of the individual variables in textile sector was (FF/CL), measuring the relationship between the funds flow and current liability, followed by (TL/TS) and (NI/TS); These three variables are consistently ranked for textile sector. The value of the overall variables D^2 is 7.44.

9.6.2 Examining the Classification Accuracy

The classification rates for the textile sector is given in Table 9-13. The classificatory power is statistically significant compared to proportional chance model. The test statistical for the difference between the results and proportional chance is 6.61, with 0.001 significance level. Type II error is 0 (0 of 46) and Type I error is 17% (4 of 23). The overall accuracy is 94%. The discriminant model for the textile sector showed a successful classification accuracy as compared with the aggregate model. It is interested to note that neither macro-economic variables nor year dummy variables are entered the model.

Table 9-11 Within Groups Correlation Matrix - Textile Model

Var	TL/TA	NI/TS
FF/CL	-0.48	0.03
TL/TA		-0.16

Table 9-12 Relative Contribution Tests of Each Independent Variables - Textile Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	2.17	1	61.53	1
TL/TA	-1.68	2	33.28	2
NI/TS	-1.25	3	5.17	3

The Value of the overall variables D^2 is 7.44

Table 9-13 Classifying the Textile Industry Model Based On Ratios, Macro-Economic, and Year Dummy Variables

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	46	0	46
Failed	4	19	23
Error Rates	0%	17%	6%

9.6.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 9-14 and Table 9-15. Textile sector is more sensitive to the cost ratio and/or the prior probability. For example, cost ratios = 1:1 to 40:1, the type II misclassification percentages are 100%, 100%, 96%, 93%, 87% respectively. Type I misclassification percentages are rather consistent. This is perhaps due to some weak but still healthy non-failed firms in the textile industry. Relative costs for Textile model are always lower than aggregate model except when cost ratios = 40:1. Based on the chi-square test, although there is evidence that the Textile industry classify more accurately than the aggregate model, the results are not consistent. The null hypotheses H_{21} can be rejected only in very specific instances.

Table 9-14 Model Efficiency Comparisons - Textile Industry and UR aggregate Model Classification

CI:CII	1:1	10:1	20:1	30:1	40:1
Textile Model Overall Accuracy %	99	96	92	89	87
UR Aggregate %	98.8	90.7	90.0	88.0	88.5

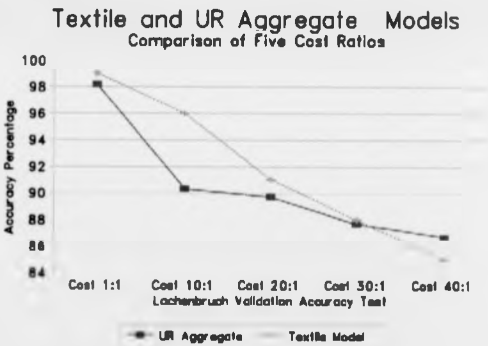
Table 9-15 Model Efficiency Comparisons - Textile industry and UR Aggregate Model Lachenbruch Hold-Out Validation

CI:CII	1:1	10:1	20:1	30:1	40:1
Textile Industry					
Non-failed (%)	46/46	46/46	44/46	43/46	40/46
Failed	12/23	19/23	19/23	19/23	19/23
Overall %	99	96	91	88	85
Textile model					
$EC_{textile}$	**0.014**	**0.05**	**0.13**	**0.21**	**0.28**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	4.14	6.4	4.6	4.28	4.25
EC_{UR} Aggregate	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
Textile Model %	100	100	100	100	100
UR Aggregate %	128	240	123	109	100
T Test *					
T-Value	**3.668c**	**2.056b**	0.201	0.04	0.082
Significance	0.055	0.152	0.654	0.841	0.220

* T-Test Comparison Between Textile industry and UR aggregate model.

b = Statistically different for $\alpha = 0.20$ c = Statistically different for $\alpha = 0.10$.

Figure 9-3



In order to test hypothesis of H_{22} 13 failed and 26 non-failed textile companies from years 1975 to 1980 were used to develop textile failure prediction ex post model. The predictive ability of the model was tested against the 30 companies from years 1981 to 1985, of which were 10 failed and 20 non-failed. The coefficients and other statistics of ex post Textile model are shown as follows:

$$Z = 3.40 + 0.98(FF/CL) - 0.09(TL/TA) - 1.47(NI/TS)$$

The statistical significance of the computed function: The computed F-statistic for this textile function is 20.48 while the tabulated value for $F(3,35) = 6.74$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed textile model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 9-16. This Table shows that the highest correlation is (-0.51) between FF/CL and TL/TA.

9.6.4 Relative Contribution of Ratios

The most important of the individual variables in textile sector was (FF/CL). These three variables are consistently ranked for textile sector. The value of the overall variables D^2 is 7.49.

9.6.5 Ex post and Ex Ante Sample Test

Table 9-18 and Table 9-19 present the classification matrices for the ex post and ex ante samples, respectively. Table 9-18 shows that the textile model correctly classified 95% of all the firms in the ex post example. Type II error is 0% and Type I error is 15%. The overall error rate is 5% for the ex post of textile sample. The upward bias in the textile result for the Lachenbruch validation sample bias test is identical to the original sample (95% vs 95%), indicating that the results are not all sensitive to sample bias. Table 9-19 shows that the model correctly classified 93.4% of all the textile firms in the ex ante sample. Zero non-failing and two failing firms were misclassified, i.e., 0% type II error and 20% type I error. The overall deterioration between ex post and ex ante sample is only 1.6 percent. These results indicate that focusing on one single industry is reasonably analogous to using industry relative ratios in samples including several industries.

Table 9-16 Groups Correlation Matrix - Textile Model

Variable	TL/TA	NI/TS
FF/CL	-0.51	0.13
TL/TA		-0.18

Table 9-17 Relative Contribution Tests of Each Independent Variables - Textile Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	2.43	1	75.32	1
TL/TA	-1.30	2	23.36	2
NI/TS	-1.02	3	1.3	3

The Value of the overall variables D^2 is 7.49

Table 9-18 Classifying the Ex Post Sample - Using Textile Model

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	26	0	26
Failed	2	11	13
Error Rates	0%	15.3%	5.1%

Table 9-19 Predicting the Ex Ante Sample - Using Textile Model

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	20	0	20
Failed	2	8	10
Error Rates	0%	20%	6.6%

9.6.6 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each model efficiency comparisons under five different input misclassification costs is shown in Table 9-20 and 9-21. At the assumed relative cost ratio from 1:1 to 40:1, the number of type I errors decreases from 43% to 15% while type II errors increases from 1% to 12%. Table 9-21 shows that at the assumed relative cost ratio of one to one, use of the Textile model saves 33 percent relative to the best IRR1 model. If the cost ratio is changes to 10 to one, a user would achieve a cost savings of 35 percent over the best IRR1 model. However, if the cost ratios changes to 20:1, 30:1 and 40:1, use of the IRR1 model saves 16, 16 and 70 percent respectively to the textile model. The textile model performed the different results according to various cost ratios if compared with IRR1 model in these comparisons (see: Table 9-21). It is interest to note that the Textile sector is not sensitive to the cost ratio in the ex ante sample test. The chi-square test gives no evidence to reject the null hypotheses H_{22}.

Table 9-20 Model Efficiency Comparisons Between Textile Industry and IRR1 - Ex post Sample Classification One Year BF

CI:CII	1:1	10:1	20:1	30:1	40:1
Textile Model					
Non-failed	100	100	100	92	92
Failed	57	85	85	85	85
Overall %	99	96.4	94.2	89	88
IRR1 (Ex Post)	98.6	94.4	91.8	91.0	92.4

Table 9-21 Model Efficiency Comparisons Between Single (Textile) Industry and IRR1 - Ex Ante Sample Prediction One Year BF

CI:CII	1:1	10:1	20:1	30:1	40:1
Non-failed	20/20	20/20	20/20	20/20	18/20
Failed	8/10	8/10	8/10	8/10	8/10
Overall %	99.4	95.2	92.8	90.4	85.5
Textile model					
$EC_{Textile}$	**0.006**	**0.06**	**0.12**	**0.18**	**0.33**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	9.66	5.33	5.08	5.00	3.6
IRR1 (Ex Ante Sample)					
EC_{IRR1}	**0.008**	**0.081**	**0.103**	**0.155**	**0.194**
Relative Cost Ratios					
Textile Model %	100	100	116	116	170
IRR1 Model %	133	135	100	100	100
T-Test *					
T-Value	0.199	0.019	0.001	0.089	0.427
Significance	0.656	0.890	0.971	0.766	0.513

* T-Test Comparison Between Textile Industry and IRR1 model In the Ex Ante Prediction.

9.7 Other Manufacturing Industry

A summary of the coefficients and statistics on the basis of 20 failed and 40 non-failed companies in the other manufacturing companies is presented as follow:

$$Z = 0.26 + 0.59(FF/CL) - 3.21(IC/TS) - 2.91(NI/TS) - 1.14(OP/TP)$$

The statistical significance of the computed function: The computed F-statistic for this function is 28.46 while the tabulated value for $F(4,55) = 5.40$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed other manufacturing model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 9-22. This Table shows that the highest correlation is (-0.48) between FF/CL and OP/TP.

9.7.1 Relative Contribution of Ratios

Table 9-23 shows that the relative contribution of each variable is not consistently ranked in each method. Taking into account the ratios in order in which they appear in the function, the failure profiles of the other manufacturing sector can be expressed by FF/CL, IC/TS, NI/TS and OP/TP based on the standardized coefficients. The value of the overall variables D^2 is 9.0.

9.7.2 Examining the Classification Accuracy

The classificatory power of the other manufacturing model is statistically significant different to proportional chance model, at the 0.001 significance level. Table 9-24 presents the model correctly classified 95% of the all the firms in the other manufacturing sample. Type II error is 0% and Type I error is 15%. The overall error rate is only 5%. The upward bias in the other manufacturing model appears to be slight since the Lachenbruch results are only two percent worse. The discriminant model for the manufacturing sector was a fairly successful when compared to the aggregate model one year prior to failure (95% vs 91%).

Table 9-22 Within Groups Correlation Matrix - Other Manufacturing Industry Model

Var	IC/TS	NI/TS	OP/TP
FF/CL	-0.43	0.06	-0.48
IC/TS		-0.09	0.32
NI/TS			-0.16

Table 9-23 Relative Contribution Tests of Each Independent Variables - Other Manufacturing Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
FF/CL	1.64	2	27.24	2
IC/TS	-1.89	1	29.87	1
NI/TS	-1.60	3	4.56	4
OP/TP	-1.49	4	16.87	3

The Value of the overall variables D2 is 9.00

Table 9-24 Classifying the Other Manufacturing Industry Model Based On Ratios, Macro-Economic, and Year Dummy Variables

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	40	0	40
Failed	3	17	20
Error Rates	0%	15%	5%

9.7.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each other manufacturing model efficiency comparisons under various costs ratios is shown in Table 9-25. The comparison between the relative cost ratios is made in Table 9-26. Table 9-26 shows that the function under five various input misclassification costs of other manufacturing model performed better than that of the aggregate model one year prior to failure. The other manufacturing sector is not statistically different from the aggregate model according to the chi-square test. Thus, the hypotheses H_{23} cannot be rejected.

Table 9-25 Model Efficiency Comparisons - Other Manufacturing Industry Classification

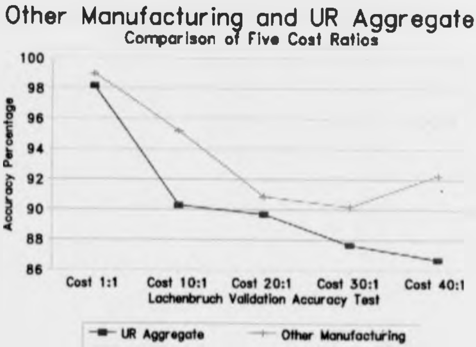
CI:CII	1:1	10:1	20:1	30:1	40:1
Other Manufacturing Model					
Overall Accuracy %	99	95.0	96.2	95.2	92.3
UR Aggregate Model	98.8	90.7	90.0	88.0	88.5

Table 9-26 Model Efficiency Comparisons - Other Manufacturing Model Lachenbruch Validation

CI:CII	1:1	10:1	20:1	30:1	40:1
Other Manufacturing					
Non-failed %	40/40	40/40	39/40	38/40	38/40
Failed	13/20	16/20	16/20	17/20	18/20
Overall %	99	95.2	90.9	90.2	92.3
$EC_{Manufacturing}$	**0.010**	**0.06**	**0.14**	**0.18**	**0.17**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	5.80	5.3	4.35	5.0	7.0
EC_{UR} Aggregate	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
Other Manufact. %	100	100	100	100	100
UR Aggregate %	180	200	114	127	164
T-Test *					
T-Value	0.304	1.307	0.259	0.366	1.307
Significance	0.581	0.253	0.611	0.545	0.253

* T-Test Other Manufacturing industry and UR aggregate model.

Figure 9-4



9.8 Miscellaneous Sector

A summary of the coefficients and statistics on the basis of 25 failed and 50 non-failed companies in the trading sector is presented as follow:

$$Z = -1.93 - 0.25(TD/TA) - 1.62(OP/TP) + 14.18(QA/TA) + 2.79(Log(TA))$$

The statistical significance of the computed function: The computed F-statistic for this function is 43.81 while the tabulated value for $F(4,70) = 5.20$. The model was statistically significant at better than $\alpha = 0.001$. Thus, this overall function indicate that the constructed trading model possesses a highly significant discriminating power. All of the variables were highly significant better than 0.05 percent. The within groups correlation which is shown in Table 9-27. This Table shows that the highest correlation is (0.36) between TD/TA and OP/TP.

9.8.1 Relative Contribution of Ratios

Table 9-28 shows that the relative contribution of each variable is consistently ranked in each method. TD/TA and OP/TP made the highest contribution, and the Log(TA) contribution the least. Taking into account the ratios in order in which they appear in the function, the failure profiles of the trading sector can be expressed by FF/CL, IC/TS, NI/TS and OP/TP.

9.8.2 Examining the Classification Accuracy

The classificatory power of the trading model is statistically significant different to proportional chance model, at the 0.001 significance level. Table 9-29 presents the model correctly classified 95% of the all the firms in the trading companies. Type II error is 8% (4 of 46) and Type I error is 0%. The overall error rate is only 5%. The result for the Lachenbruch validation sample bias test is the same as to the original sample (95% vs 95%). The discriminant model for the trading sector was a fairly successful when compared to the aggregate model one year prior to failure (95% vs 91%). However, neither macro-economic nor year dummy variables entered the model, suggesting this sector is not influenced by macro-economic or time series issues.

Table 9-27 Within Groups Correlation Matrix - Trading Model

Var	OP/TP	OA/TA	Log (TA)
TD/TA	0.36	-0.08	0.11
OP/TP		-0.11	-0.04
OA/TA			-0.09

Table 9-28 Relative Contribution Tests of Each Independent Variables - Miscellaneous Model

Variables	Standardized Coefficients	Ranked	Mosteller & Wallace's %	Ranked
TD/TA	-3.1	1	67.49	1
OP/TP	-1.74	2	22.37	2
OA/TA	1.41	3	7.82	3
Log(TA)	1.22	4	2.30	4

The Value of the overall variables D2 is 10.96

Table 9-29 Classifying the Trading Industry Model Based On Ratios, Macro-Economic, and Year Dummy Variables

Actual Groups	Classified As: Non-failed	Failed	Total
Non-failed	46	4	50
Failed	0	25	25
Error Rates	8%	0%	5.3%

9.8.3 Sensitivity to Prior Probabilities and Misclassification Costs

The results of each trading model efficiency comparisons under various costs ratios is shown in Table 9-30. The comparison between the relative cost ratios is made in Table 9-31. Table 9-31 shows that the discriminant model for the Miscellaneous sector reported a satisfactory stable level of prediction accuracy compared with the aggregate model one year prior to failure for the cost ratios. However, the chi-square test yields no evidence to reject the null hypotheses H24 above.

Table 9-30 Model Efficiency Comparisons - Miscellaneous Industry and UR Aggregate Model Classification

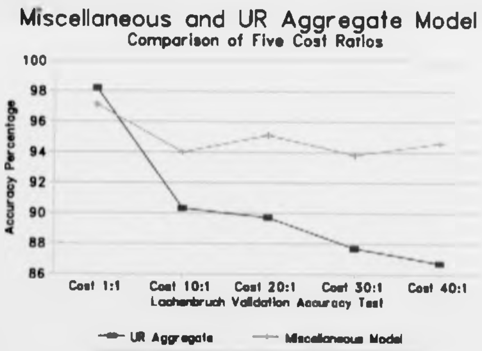
CI:CII	1:1	10:1	20:1	30:1	40:1
Miscellaneous Model					
Overall %	99.2	94.0	95.1	95.9	95.5
UR Aggregate Model	98.8	90.7	90.0	88.0	88.5

Table 9-31 Model Efficiency Comparisons - Miscellaneous and UR Aggregate Model Lachenbruch Hold-Out Validation

CI:CII	1:1	10:1	20:1	30:1	40:1
Miscellaneous Industry					
Non-failed %	50/50	46/50	46/50	44/50	44/50
Failed	17/25	25/25	25/25	25/25	25/25
Overall %	97.1	94.0	95.1	93.8	94.6
$EC_{miscellaneous}$	**0.009**	**0.08**	**0.08**	**0.12**	**0.12**
EC_{prop}	0.058	0.32	0.61	0.90	1.19
Times	6.44	4.0	7.62	7.50	9.91
EC_{UR} Aggregate	**0.018**	**0.12**	**0.16**	**0.23**	**0.28**
Relative Cost Ratios					
Mis. Model %	100	100	100	100	100
UR Aggregate %	200	150	200	191	233
T-Test *					
T-Value	0.692	2.591	1.855	0.562	0.841
Significance	0.406	0.107	0.173	0.453	0.359

* T-Test Comparison Between Miscellaneous industry and UR aggregate model.

Figure 9-5



9.9 A Comparison Between The Aggregate and Industry-Specific Models

The purpose of comparing the aggregate model with industry-specific models is to test hypothesis 23 which states that "there is no difference in the predictive abilities of the aggregate model and the industry-specific models". The comparison is made between the two functions of each of models and includes the important measures of efficiency. The classification accuracy between the aggregate and industry-specific models is presented in Table 9-32. The model efficiency comparison under five input misclassification costs between the aggregate and industry-specific models validation tests is presented in Table 9-33. Table 9-32 and Table 9-33 show that the industry-specific models is superior to the aggregate model for the first year prior to failure. Therefore, the results of this comparison reject the null hypotheses above. Industry differences are important, and analysts working in this field must adopt one of the strategies for dealing with industrial differences.

Table 9-32 The Classification Accuracy Between the Aggregate and Industry-Specific Models

CI:CII Models	1:1 Percentage	10:1 of	20:1 Correct	30:1 Classification	40:1
UR Aggregate	98.8%	90.7%	90.0%	88.0%	88%
Contracting	100%	100%	100%	100%	100%
General-Engineering	100%	100%	100%	100%	100%
Textile	99%	96%	92%	89%	88%
Other Manufacturing	99%	95%	96%	95%	92%
Miscellaneous	99%	94%	95%	96%	96%

Table 9-33 Model Efficiency Comparisons Between the Aggregate and Industry-Specific Models Lachenbruch Validation

CI:CII Models	1:1 Percent of	10:1 Correct	20:1 Classification	30:1	40:1
$EC_{\text{UR Aggregate}}$	180	120	160	230	280
$EC_{\text{Contracting}}$	0	0	0	0	0
$EC_{\text{Engineering}}$	0	0	0	0	0
EC_{Textile}	140	50	130	210	280
$EC_{\text{Manufacturing}}$	100	60	140	180	170
$EC_{\text{Miscellaneous}}$	90	80	80	120	120

9.10 Results Two and Three Years Prior

9.10.1 Results Two and Three Years Prior - Contracting Industry

The overall contracting model was statistically significant at better than $\alpha = 0.001$ two and three years before failure, respectively. As expected, with the cost ratios 1:1, the overall accuracy falls from the one year 100% to 98% and 97% in year 2 and year 3 respectively. This contracting model shows better accuracy for failed, non-failed and overall sample for year two and year three. Table 9-34 and Table 9-35 present model efficient comparisons under five various error costs classification and Lachenbruch hold-out Test.

Table 9-34 Model Efficiency Comparisons - Contracting Industry Classification and Lachenbruch Validation Test Second Year BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	100	100	95	95
	Failed	37	100	100	100	100
	Overall %	98.1	100	100	98	98
2	Non-failed	100	91	91	91	91
	Failed	37	91	100	100	100
	Overall %	98.1	91	94.4	95	96

Table 9-35 Model Efficiency Comparisons - Contracting Industry Classification and Lachenbruch Validation Test Third Years BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	91	86	73	55
	Failed	0	38	64	64	73
	Overall %	97	78	78	69	65
3	Non-failed	100	91	86	73	55
	Failed	0	0	64	64	64
	Overall %	97	69	78	69	60

9.10.2 Results Two and Three Years Prior - General-Engineering Industry

The overall General-Engineering model was statistically significant at better than α = 0.001, two and three years BF. Among the discriminant variables the significance test for the individual shows that their significance level are less than 0.05. As expected, with the cost ratios of 10:1, the overall accuracy falls from the one year 100% to 95% and 82% in year two and year three. This General-Engineering model shows good classification accuracy and Lachenbruch hold-out test year two and three BF. Table 9-36 and Table 9-37 present model efficient under five different error costs. The results of tests exhibit more stable classification rates second and third year BF.

Table 9-36 Model Efficiency Comparisons - General-engineering Industry Classification and Lachenbruch Validation Test Second Years BF

Years Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	100	100	100	100
	Failed	67	78	89	89	89
	Overall %	99	95	96	95	94
2	Non-failed	100	100	100	100	100
	Failed	67	78	78	78	78
	Overall %	99	95	92	89	88

Table 9-37 Model Efficiency Comparisons - General-Engineering Industry Classification and Lachenbruch Validation Test Third Years BF

Years Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	94	84	83	78
	Failed	11	45	66	89	89
	Overall %	97.4	82	77	86	84
3	Non-failed	94	94	86	83	78
	Failed	11	33	64	89	89
	Overall %	92	80	78	86	84

9.10.3 Results Two and Three Years Prior - Textile Industry

The overall textile model was statistically significant at better than $\alpha = 0.001$ two and three years prior to failure. Among the discriminant variables the significance test for the individual indicates that their significance level are less than 0.05. Textile model two and three years BF, with the cost ratios of 10:1, give 90% and 87% accuracy, respectively in Table 9-38 and Table 9-39. This textile model presents well accuracy for year two and three BF. Table 9-39 presents the percentage of firms correctly classified validation test two and three years BF using textile model. The results of Lachenbruch validation tests show more consistent classification accuracy second and third year BF to the original sample.

Table 9-38 Model Efficiency Comparisons - General- Textile Industry Classification and Lachenbruch Validation Test Second Years BF

Years Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	93	85	85	85
	Failed	43	78	91	91	96
	Overall %	98.3	90	87	88	91
2	Non-failed	100	91	85	85	85
	Failed	39	70	87	91	91
	Overall %	98.2	86	86	88	88

Table 9-39 Model Efficiency Comparisons - Textile Industry Classification and Lachenbruch Validation Test Third Years BF

Years Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	98	91	85	72
	Failed	8	52	74	79	83
	Overall %	97.3	87	85	82	78
3	Non-failed	100	98	91	79	70
	Failed	8	52	74	74	78
	Overall %	97.3	87	85	76	74

9.10.4 Results Two and Three Years Prior - Other Manufacturing Industry

The overall other manufacturing model was statistically significant at better than α = 0.001 two and three years prior to failure. Among the discriminant variables the significance test for the individual indicates that their significance level are less than 0.05. Other manufacturing model two and three years BF, with the cost ratios of 10:1, give 87% and 100% accuracy, respectively in Table 9-40 and Table 9-41. This other manufacturing model presents good accuracy for year two and three BF. In the bottom half of Table 9-40 and Table 9-41 present the percentage of firms Lachenbruch validation test two and three years BF. The results of validation tests show more consistent classification accuracy to the original sample both in overall and non-failed accuracy.

Table 9-40 Model Efficiency Comparisons - Other Manufacturing Industry Classification and Lachenbruch Validation Test Two Years BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	87	87	87	85
	Failed	25	75	85	90	95
	Overall %	97.8	84	87	89	90
2	Non-failed	100	87	87	85	85
	Failed	25	65	85	90	95
	Overall %	97.8	82	87	87	90

Table 9-41 Model Efficiency Comparisons - Other Manufacturing Industry Classification and Lachenbruch Validation Test Third Years BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	100	82	65	53
	Failed	5	20	50	75	85
	Overall %	97.2	81	71	70	70
3	Non-failed	100	100	83	63	50
	Failed	5	15	40	70	85
	Overall %	97.2	80	67	66	69

9.10.5 Results Two and Three Years Prior - Trading Industry

The overall other manufacturing model was statistically significant at better than α = 0.001 two and three years prior to failure. Among the discriminant variables the significance test for the individual indicates that their significance level are less than 0.05. Trading model two and three years BF, with the cost ratios of 10:1, give 96% and 98% accuracy, respectively in Table 9-42 and Table 9-43. This trading model presents good accuracy for year two and three BF. In the bottom half of Table 9-40 and Table 41 are shown the percentage of firms Lachenbruch validation test two and three years BF. The results of tests show more consistent classification accuracy to the original sample both in overall and non-failed accuracy.

Table 9-42 Model Efficiency Comparisons - Trading Industry Classification and Lachenbruch Validation Test Two Years BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
2	Non-failed	100	96	94	94	94
	Failed	68	84	92	92	92
	Overall %	99	93	94	93	93
2	Non-failed	98	96	94	94	94
	Failed	64	84	88	92	92
	Overall %	97	93	92	93	93

Table 9-43 Model Efficiency Comparisons - Trading Industry Classification and Lachenbruch Validation Test Third Years BF

Year Prior to Failure	CI:CII	1:1	10:1	20:1	30:1	40:1
3	Non-failed	100	98	94	92	84
	Failed	36	76	84	88	88
	Overall %	98	93	91	91	86
3	Non-failed	100	94	90	88	80
	Failed	36	72	80	84	88
	Overall %	98	89	86	86	84

9.11 Summary and Conclusions

In this chapter, results of this study show enhanced corporate failure prediction, as follows:

1. Prediction of failure appeared to be improved by taking into account financial characteristics of each specific-industry, such as Contracting, Engineering and Textile industries.

2. The discriminant functions of the five industries exhibited a higher predictive ability than that of the aggregate model. (see Table 9-32 and Table 9-33). However, the size of firms in the sample in the Contracting and General-Engineering industries is small. Smaller firms (Contracting and General-Engineering) achieved better predictive accuracy one year prior to failure compared to larger firms (Textile, Other Manufacturing and Trading). This may be attributable to the fact that small firms, in this study, have more homogeneous financial characteristics than larger firms. Conclusions from such a small sample and a higher classification accuracy might not be generalizable.

3. Financial variables which classify certain specific industries successfully may not be guaranteed to be successful when they are applied to other industries. Therefore, certain variables that are appropriate for the prediction of failure in one industry may not be appropriate for others. For example, if one wants to examine the potential for failure of a clothing manufacturing, one should use the prediction model derived from the financial attribute of the Textile industry including appropriate variables.

4. Early studies by Gupta [1969] and Gupta and Huefner [1972] have demonstrated that different industries have different financial ratios. It would be valuable to identify appropriate sets of variables for different types of industry. It is apparent from this research that different industries require

different financial characteristics. For instance, the Contracting group included the FF/CL, NI/TA, OP/TA and CA/TA variables while General-Engineering included the CG, YR11, RE/TA and YR5 variables. The FF/CL, TL/TA and NI/TS variables are included within Textile group while FF/CL, IC/TS, NI/TS and OP/TP variables are included within the other manufacturing group. TD/TA, OP/TP, OA/TA and Log(TA) variables are included in the Miscellaneous group. These differences in discriminant variables resulted to industry characteristics. However, FF/CL variable makes an important contribution to the Contracting, Textile and Other Manufacturing groups.

5. The relative importance of the individual variables varied between different sets of ratios and industries. Statistical tests on the financial variables have not been conclusive in most previous discriminant studies because of the normality assumptions for financial ratios. The contribution of each financial variable to each industry prediction model was quite consistent among industries, except for the other manufacturing industry.

6. Classification accuracy rates for each industry varied over different sets of variables. In general, the predictive accuracy of each specific industry appears to yield better results than that of the aggregate model. The relatively similar accuracy of the textile group can be possibly explained by the fact that the textile sample used in this research consisted of many distressed non-failed firms.

7. Sensitivity to five various input misclassification costs for contracting and General-Engineering and Miscellaneous industries are, in general, less sensitive than the aggregate model.

8. Inclusion of the macro-economic variables in this study did not improve classification accuracy of the model. The macro-economic variables (interest

rate, annual inflation, real GNP, and industrial production) included in this study may be too general in nature to use as a macro-economic variables. Testing of economic variables that reflect economic conditions in regions of the country or one reflecting economic conditions within a type of specific industries may be a possible path of future study. Such a variable could be defined as the unemployment rate for a region or for an specific industry. However, other macroeconomic variables could be developed to represent the specific industries and overall economy. Testing of such variables could lead to a prediction of failure model which is not specific to the time period used to develop the models. We focus that year dummy variables contributed only marginally to the Textile industry.

9. Relative costs from each specific industry are lower than those from the proportional chance model even when the cost ratios is varied at the five various levels.

10. Generalizability of the industry specific results is limited to firms from the data base (Datastream) and to data from the years studies (1974-1985). An empirical study is limited in its generalizability unless the sample is representative of the entire population. Using a variety of data sources would increase the possibility of generalizability of results. In particular the behaviour of small firms is known to differ from the Datastream companies.

11. Industrial differences are important, and an analyst must develop a strategy which takes such differences into account. If there is sufficient data an industry specific model is one strategy. The other strategy is to adjust the ratios for industry differences using the relative ratios form, and the industry mean as the benchmark.

Chapter 10: Summary and Conclusions

10.1 Introduction

Empirical failure prediction studies have shown how financial ratios and various other variables can be successful in predicting financial failure. However little attention in financial distress research has been given to the behaviour of failure prediction models over time and over various sectors. In particular it appears that models are unstable with respect to out-of-sample classifications accuracy. Our investigation has examined how use of industry relative ratios, consideration of homogeneous economic conditions, and the estimation of industry-specific models have each been helpful in developing stable business failure models.

There have been prior empirical tests using samples of Australian and American companies of the efficiency of various types of models which include factors such as (i) industry relative ratios, (ii) business cycles, and (iii) industry-specific models. Izan [1984] and Platt and Platt [1990] tested the use of industry relative ratios. Mensah [1984] analysed business cycles. Altman [1973], Marais and Harris [1977] and Pantalone and Platt [1987b] evaluated specific industries.

In spite of this prior literature, our knowledge of the information content and predictive ability of industry relative ratios and business cycles is still fragmentary. Firstly, the concept of industry relative ratios is uncertain. There is a definitional choice between industry median ratios and industry mean ratios. For example, Platt and Platt used industry mean ratios in their American data, whereas Izan [1984] used industry median ratios in his Australian data. The Platt and Platt's [1990] results using industry mean ratios show at a more stable and consistent predictive ability between ex post and ex ante sample. The results from Izan's [1984] using industry median ratios shows less stability and consistency between ex post and ex ante when compared to Platt and Platt's [1990] results. Inevitably because of different data sets there may be limited generalizability over time and across industries. In particular, evidence from USA and Australian data may not be generalisable to the UK-based context. This study has remedied this deficiency. Thirdly, economic fluctuations in the USA, Australian, and the UK are different, and a model developed using industry relative ratios or in certain parts of the business cycle may not be successful when applied to the UK. Unlike the above studies this work has considered time series and across industries instability problems simultaneously.

In an attempt to fill a gap in the literature, this study has developed a class of UK-based stable failure prediction models. (1) Using industry relative (mean and median) ratios to tests if the predictive ability of the industry relative ratios are better than that of the unadjusted models, (2) the predictive ability of three methods (IRR1, IRR2, and UR) in three business cycles [(expansion, IRR1B1, IRR2B1, and URB1), recession (IRR1B2, IRR2B2, and URB2), and recovery (IRR1B3, IRR2B3, and URB3)] are better than that of unadjusted ratios aggregate model, (3) the predictive ability of each specific industries are greater than that of unadjusted ratios aggregate model. A summary of the results of this study, its conclusions and suggestions for future research are now presented.

10.2 Variables' Design and Their Distribution

Initially, of 42 financial ratios, one was excluded because of missing values. An examination of the distributional properties of the ratios for failed and non-failed firms showed the results of the study do not support the assumption of multivariate normality. Since normality of the variables is required for valid application of multivariate discriminant analysis, winsorization and Box and Cox [1964] methods of transformation were used to transform each ratio's distribution to approach normality. However, no general guide-lines were offered or principles established as to which transformation was appropriate in a particular instance. This bears out the conclusions of Deakin, [1976]. A close relationship between kurtosis and skewness statistics was observed. Those ratios with a low skewness also had a low kurtosis. The examination of the distributional properties of the ratios showed that most of them were not normally distributed. The study showed that only WC/TA and TL/TA appeared to have a normal distribution. Most ratios when transformed and approached of a normal distribution except for cash position ratios, [for example, TC/TS, TC/TA, and TC/CL] For these ratios the positive value mode was located at zero which was also the lower bound and no amount of transformations would normalise. In general, most of the ratios, the histograms and normal probability plot of the non-failed group appeared to be closer to normality than those of the failed group. This was more particularly seen as the companies approach failure. However, univariate normality of ratios does not guarantee multivariate normality. In the case of most ratios, there was a great deal of improvement although not enough to accept the null hypotheses of no departure from normality.

10.3 Univariate (Profile) Analysis

The univariate analysis has two major objectives in this study: (1) to evaluate the potential of ratio analysis through the visual inspection of profiles to identify the characteristics of failed and non-failed firms; (2) to identify whether according to the univariate analysis any ratio or group of ratios is able to distinguish consistently between failed and non-failed firms. This study shown there is a clear difference between the financial ratios of failed and non-failed firms on the basis of means, as far back as three years prior to failure. For example, the best five financial indicators for the use of industry relative ratios in the profile analysis are presented as follows: FF/CL, IC/TS, NI/NW, OP/TP, TS/NPA. It is perhaps worthwhile discussing the failed and non-failed group of FF/CL ratios because it is very significant in many models. The FF/CL appear to be relatively good univariate predictor of failure. In general the FF/CL ratio of failed firms is lower than non-failed firms and the distributions of the two groups appear reasonably separate. Amongst the financial ratios FF/CL appears to perform best. The implication of this ratio is that the FF/CL of a failed firms, five years prior to failure, is below that of a non-failed firms and FF/CL is therefore a good indicator. Another conclusion to be drawn from this analysis is that the use of univariate techniques is extremely cumbersome. Only few ratios have been examined, it is not possible to measure directly that contribution or to determine the extent to which combinations of ratios are good predictors of corporate failure.

10.4 Factor Analysis

In order to reduce multicollinearity problem in financial ratios, and to aid the formulation and interpretation of discriminant model, factor analysis was used for each group of companies separately to extract the non-collinearity best financial ratios. The results of the analysis showed that the factor loading extracted different dimensions in business cycle and specific industries models separately. We did factor analysis but did not use it due to instability in the loading of ratios and the difficulty of interpretation of the results. Factor analysis is a problematic technique in this context.

10.5 Cluster Analysis

The possibility of using cluster analysis to re group the 16 industries, represented in this study, into more homogeneous number of groups, a device used with mixed success by other authors [Sudarsanam and Taffler, 1985] was rejected because of the instability of financial attributes over time and across industries. [see chapter 6.6.1].

However, the sample we re-grouped into broader categories (1) Contracting, (2) General-Engineering, (3) Textile, (4) Other Manufacturing, and (5) Miscellaneous industries on the basis of Standard Industry Code (SIC). The purpose of this broad classification was to get sufficient observations to examine if there are any differences in the process of business failure for groupings by industry.

10.6 Correlation Analysis

Correlation analysis computes the coefficients between variables and measures the strength of the linear relationship between two variables and highlights collinearity problems. For the 41 financial ratios, collinearity can not be avoided. Incorporation of the collinear ratios in statistical models produces the econometric disease of "multicollinearity", causing it to be difficult to interpret the partial coefficients because of inconsistent parameter estimates. The favourable implication of the collinearity of accounting ratios is that a small number of the suggested ratios will convey almost all the information contained in all other ratios. The unfavourable implication of the ratios' collinearity is that the inclusion of collinear ratios, as independent variables, which are related to a dependent variable in the same fashion, would obscure and possibly worsen the results of a multivariate analysis (Lev, 1974, p. 65). Therefore, the typical procedure, was used here as is used in almost all the multivariate studies, to exclude the highly correlated ratios. In this study, for the combination of all the firms, the highest correlation between ratios is 0.98 for the NI/TS and EBIT/TS. For the non-failed firms and failed firms respectively, the highest correlation is 0.99 for the EBIT/TS and FF/TS. The lowest correlated ratios were FF/TS and TC/CL. When the variables are highly correlated, indicating that the variables related to each other, or overlap in what they measure. If the correlations between variables are small, it is unlikely that they share common factors.

10.7. A Model Using Industry Relative Ratios and Unadjusted Ratios

This involved developing a class of UK-based predictive models using industry relative ratios to control for the effect of industry. Industry mean (IRR1) and industry median (IRR2) were selected in generating the industry relative ratio. Using industry relative ratios can standardise individual company ratios so as to reduce the heterogeneous nature of the companies.

Four pairwise comparisons (IRR1 vs UR, IRR2 vs UR, and UR vs IRR1 and UR vs IRR2) of failure prediction models were developed using stepwise discriminant and Multivariate Discriminant Analysis. In the comparison the model is developed first for the ratios form given, and then adjusted to a sub-optimal model using the second ratio form given in the pair. Thus (IRR1 vs UR) is different from (UR vs IRR1). The size of the study on UK data covering 264 failed and non-failed firms, an 11 years span, 4 macro-economic variables, 41 financial ratios and 5 broad groupings has not been exceeded. The UR model using the unadjusted data based on the historical ratios included five different variables (FF/CL, NI/TS, OP/TP, CA/TA, and IC/TS). Both IRR1 and IRR2 models included the same five variables (FF/CL, IC/TS, NI/NW, OP/TP, and TS/NPA). Three models performed on the basis of the following tests of applicability: (1) overall model statistical significance; (2) the relative importance of independent variables; (3) the Z proportional chance criterion test; (4) the ex post and ex ante classification accuracy; (5) the Lachenbruch validation and split sample technique test; (6) Conover T test .

It was found that when the IRR1 model is then constrained to include the same five ratios as in the UR model, the overall accuracy of IRR1 performs better than that of UR model in the ex ante example prediction (93% vs 89%) (see: Table 7-9 and 7-12). For the IRR2 model constrained to include the same five ratios as in the UR model, the overall accuracy of IRR2 model performs similar to that of UR model in the ex ante example prediction (89% vs 89%) (see: Table 7-18 and 7-21). Reversing the order using UR model constrained to include the same five ratios as in the IRR1 and IRR2 models, the overall accuracy of UR model performs less than that of IRR1 and IRR2 models (86% vs 92% and 86% vs 89%) respectively in the ex ante sample. (see: Table 7-29, Table 7-32, and Table 7-34). Comparison of the three best models - UR, IRR1, and IRR2 to test the first three hypotheses. Findings from above analysis and tables are:

1. The best IRR1 model is superior to the best UR model particularly in forecast validation result one year prior to failure (93% vs 89%) (see: Table 7-35). Both overall and in failed and non-failed classification, based on the sample prior proportion and equal misclassification cost. When incorporating a realistic prior probability and five different cost assumptions, the IRR1 model still dominates the UR model with respect to every combination of expected cost performance and cost ratio; except that of cost ratio = 1:1. However even this abnormal result was not statistically significant only based on chi-square test (see Table 7-36A) .

2. The best IRR2 model is only slightly superior to the best UR model. Both overall and failed and non-failed classification in the ex ante example (89% vs 89%) (see: Table 7-35). When incorporating a realistic prior probability and five different cost assumptions, the IRR2 model still slightly dominates the UR model with respect to every combination of expected cost performance and cost ratio; But, the chi square test gives no evidence to reject the null hypotheses H_2. Thus, there is no difference in the predictive ability of the IRR2 model and that of UR model (see : Table 7-36B).

3. The best IRR1 model is slightly superior to the best IRR2 model. Both overall and failed firms in the ex ante example (93% vs 89%) (see: Table 7-35). When

incorporating a realistic prior probability and five different cost assumptions, the IRR1 model still slightly dominates the IRR2 model with respect to every combination of expected cost performance and cost ratio: However, the chi-square test gives no evidence to reject the null hypotheses H_3. Thus, there is no difference in the predictive ability of the IRR1 model and that of IRR2 model (see : Table 7-36C).

Using industry mean ratios, models developed from failed and non-failed firms quoted on the UK stock exchange yielded a Type I error of 7 per cent based on the data from ex post (within sample) sample one year before failure, and also a 7 percent Type II error from ex ante (out-of-sample) example. These classification rates were stable and consistent over time and across industries one year prior to failure (as indicated by relatively similar ex-post and ex-ante results as compared to unadjusted ratios). While there was an improvement in the classification using industry relative (mean and median) ratios, the greatest improvement was for the sample of non-failed and failed firms. These classification rates were stable out of sample [see Table 7-35 and Table 7-36A, Table 7-36B, and Table 7-36C).

Therefore, the UK Z-score model using the IRR1 ratios performed well and were consistently stable from ex-post forecast to the ex-ante period. This empirical result is consistent with that of Platt and Platt's [1990] one year prior to failure. In this study, overall classification results with IRR1 and IRR2 models for the ex post sample analysis were slightly better than the UR model. However, the greatest benefit in classification rates from using IRR1 and IRR2 ratios came from the sample of ex ante firms. That is, the model using industry-relative ratios (particularly in IRR1 model) can cope with the disparity between ex post and ex ante instability.

10.8 A Model Using Industry Relative Ratios and Business Cycles

Studies using financial ratios in developing multivariate failure prediction models are numerous. With few exceptions the performance of their ex ante (out-of-sample) predictive ability worsens when considering both time series and across industries. The possible source of instability in multivariate models of failure is different macro-economic environments and industry effects. Using industry relative ratios to control for the effect of industry and simultaneously taking into account of changing economic environment conditions over time is perhaps the greater challenge in constructing impressive failure prediction models.

Three aggregate (URAG, IRR1AG, and IRR2AG) models are developed based on the combined sample. The overall accuracy for URAG, IRR1AG and IRR2AG are 90%, 93%, and 91% respectively. IRR1AG model is superior to URAG and IRR2AG models with respect to the percentage of correct classification. However, the study has shown a high proportion of failed and non-failed firms are correctly classified during the three business cycles of the UK economy using UR, IRR1, and IRR2 models. Findings from the above three business cycles in the expansionary, recessionary, and recovery phases empirical analysis are:

1. Unadjusted ratios in the expansionary phase model (URB1) is not very significantly different from URAG aggregate model based on chi-square test, but the percentage of correct classification of URB1 model in expansionary phase is higher than URAG aggregate model under five various cost ratios assumption (see: Table 8-20).

2. IRR1B1 model in expansionary phase performed better than that of IRR1AG and URAG aggregate models one year prior to failure. The Chi-square test

gives significant evidence to reject the null hypotheses H_5 and H_6. (see Table 8-25).

3. IRR2B1 model in expansionary phase performed consistently better than that of IRR2AG and URAG combined models. The comparison between the measures of efficiency shows that this model outperforms the IRR2AG and URAG aggregate models for all cost ratios 1:1. However, the Chi-square test gives no significant evidence to reject the null hypotheses H_7 and H_8.

Findings from the above business cycles in the recessionary phases empirical analysis are:

4. Unadjusted ratios in the recessionary phase (URB2) is not statistically different from URAG aggregate based on chi-square test. The percentage of correct classification of URB2 model in recessionary phase is higher than URAG aggregate model for low cost ratios, that is cost ratios under 20:1 (see: Table 8-35).

5. IRR1B2 model in recessionary phase performed better than that of IRR1AG and URAG aggregate models with respect to the percentage of correct classification. The Chi-square test gives no significant evidence to reject the null hypotheses H_{10}.

6. IRR2B2 model in recessionary phase performed better than that of IRR2AG and URAG combined models when cost ratios vary from 10:1 to 40:1. However, the Chi-square test gives no consistently significant evidence to reject the null hypotheses H_{12} and H_{13}.(see Table 8-45).

Findings from the above three business cycles in the recovery phases empirical analysis are:

7. Unadjusted ratios in the recovery phase model (URB3) is not significantly different from URAG aggregate model based on chi-square test, but the percentage of correct classification of URB3 model in recovery phase is higher than URAG aggregate model (see: Table 8-50).

8. IRR1B3 model in recovery phase performed better than that of IRR1AG and URAG aggregate models with respect to the percentage of correct classification. The Chi-square test gives no significant evidence to reject the null hypotheses H_{15}. Comparison with the URAG aggregate model, the chi-square test gives significant evidence to reject the null hypotheses H_{16} except that cost ratios = 1:1. (see Table 8-55).

9. IRR2B3 model in recovery phase performed similar to that of IRR2AG and URAG combined models. The Chi-square test gives no significant evidence to reject the null hypotheses H_{17} and H_{18}. (see Table 8-60).

The results of classification accuracy for the expansionary, recessionary, and recovery phases are excellent using IRR1 model rather than IRR2 and UR models again. The Mahalanobis D^2 distance and classification accuracy was higher for expansionary and recessionary periods, and was lowest for the recovery period using IRR1 and IRR2 ratios one year prior to failure. This means that failing companies may be easier to identify in economic expansion and recession periods than in the period followed by an economic recovery.

In general, using UR, IRR1, and IRR2 ratios over three different economic conditions appear to be a better at discriminating than that of the aggregate model. The Mahalanobis D^2 using URB1 ratios were 12.38 for the expansionary period, 7.78 for the recessionary period (URB2), and 8.43 for the recovery period (URB3). In contrast, the Mahalanobis D^2 using IRR1B1 and IRR2B1 ratios were 20.63 and 13.35

for the expansionary phase, 9.24 (IRR1B2) and 12.10 (IRR2B2) for the recessionary phase, 8.92 (IRR1B3) and 5.90 (IRR2B3) for the recovery phase respectively.

The significant variables in the expansionary period using URB1 ratios are FF/CL and FF/TA ratios. When using IRR1B1 ratios are WC/TA, CA/TS, OP/TP, and NI/NW ratios, and when using IRR2B1 ratios are FF/CL, OP/TP, and TS/TA ratios. In the recessionary period, the significant variables using URB2 ratios are NI/TS, EBIT/TA, TL/TA, and IC/TS ratios. When using IRR1B2 ratios are TD/TA, FF/TA, NI/TA, IC/TS, and CA/TA. When using IRR2B2 ratios are TD/TA, RE/TA, EBIT/TA, IC/TS, and OP/TP. However, in the recovery phase, the significant variables using URB3 ratios are TD/TA, FF/CL, NI/TS, TS/NPA, and Log(TA). When using IRR1B3 ratios are NI/NW, FF/CL, IC/TS, OP/TA, and CA/TA. When using IRR2B3 ratios are FF/CL, NI/TS, Log(TA), TS/TA, and OP/TP. Despite this wide variation in important ratios, as the macro-economic environment changes, one consistent finding was the superiority of the IRR1 form.

10.9 Industry-Specific Models

In this study, we grouped total observations across industries into Contracting, General-Engineering, Textile, Other Manufacturing, and Miscellaneous sectors, the five groupings were based on SIC codes to develop each industry-specific model. This is a further examination of each industry's differences as compared to an aggregate model with respect to the percentage of the classification accuracy. 264 failed and non-failed firms are included in this study according to industries and across industries, forty-one financial ratios, four macro-economic variables, and eleven year dummy variables are used to examine the differences between each industry-specific model and the UR aggregate model.

Findings from the above industry-specific models indicated as follows:

1. The results of Contracting model performed better than that of URAG aggregate model one year prior to failure. The Chi-square test gives significant evidence to reject the null hypotheses H_{19}. There is no difference in the predictive ability between the **Contracting** industry samples and the unadjusted ratios aggregate model (**URAG**) (see Table 9-5).

2. The results of **General-Engineering** (**GE**) industry performed better than that of (URAG) aggregate model one year prior to failure. The Chi-square test gives significant evidence to reject the null hypotheses H_{20}. There is no difference in the predictive ability between the General-Engineering (GE) model and the unadjusted ratios aggregate model (URAG) (see Table 9-10).

3. The results of Textile model performed better than that of unadjusted ratios aggregate model (URAG) with respect to the percentage of classification accuracy. However, the Chi-square test gives no significant evidence to reject the null hypotheses H_{21}. Comparison with the (URAG) aggregate model, only two pair of comparison between Textile model and (URAG) aggregate shows evidence of a statistical difference in predictive ability ($T = 3.668$ and $T = 2.056$). Thus, in general there is no difference in the predictive ability between Textile model and unadjusted ratios aggregate models (see Table 9-15).

4. The results of a single **Textile** model performed similar to that of IRR1 model in both ex post (95% vs 93%) and ex ante (93% vs 93%) example when sample prior proportion and equal costs are used. The comparison between the measures of efficiency shows that the single Textile model outperforms the IRR1 model in the ex ante example except for cost ratios from 20:1 to 40:1. However, the Chi-square test gives no consistently significant evidence to reject the null hypotheses H_{22} (see Table 9-21).

5. The results of Other Manufacturing model performed better than that of unadjusted ratios aggregate model with respect to the percentage of classification accuracy. However, the Chi-square test gives no significant evidence to reject the null hypotheses H_{23} (see Table 9-26).

6. The results of Miscellaneous industry performed better than that of unadjusted ratios aggregate model with respect to the percentage of classification accuracy. However, the Chi-square test gives no significant evidence to reject the null hypotheses H_{24} (see Table 9-31).

7. It appears that financial variables which classify certain specific industries successfully are less successful when they are applied to other industries.

8. It would be valuable to identify appropriate sets of variables for different types of industry. It is apparent from this research that different industries require different financial characteristics.

9. The models for the different sectors vary in terms of the variables included: The relative importance of the individual variables varied between different sets of ratios and industries.

10. Foster [1986] has suggested that multivariate models could increase predictive power by incorporating macro-economic variables. Rose, Andrew, and Giroux [1982] make a similar recommendation. In this study, in an attempt to discover which macro-economic variables are most related to bankruptcy, we examine economic indicators suggested by economic theory. The findings show that inclusion of the macro-economic variables in this study did not improve classification accuracy of the model. The macro-economic variables (interest rate, annual inflation, real GNP, and industrial production) included in this study may be too general in nature to use as a macro-economic

variables. Because incorporating national indicators directly in a cross-sectional sample or even specific industries will not be useful in distinguishing between failing and non-failing firms, since each firm will be operating under the same conditions. Testing economic variables reflecting economic conditions in different geographical regions of the country, or even reflecting economic conditions within a type of specific industries may be a possible avenue of future study. Such variables could be, for example, the unemployment rate for a region or for an specific industry. While adverse economic conditions will hurt industry margins, industries survive even very severe local, national, or international economic downturns. However, other macro-economic variables could be developed to represent the specific industries and overall economy. Testing of such variables could lead to a bankruptcy prediction model which is not specific to the time period used to develop it.

11. Generalizability of the industry specific results is limited to firms from the data base (Datastream) and to data from the years studies (1974-1985).

Cressy [1992] examined the influence of economy- and industry-wide factors and trends in the financial ratios on the explanation of bankruptcy potential of UK small firms. He found that industry factors for each of the sectors have some importance in the explanation of bankruptcies of small businesses. The Macro-effect was examined in his paper by defining year-dummies for each of the years 1970-80. He also concluded that the year- or macro-effect alone explains a significant proportion of the variation of bankruptcy probabilities across firms, with some years much more important than others. Unfortunately, in this study, macro-economic and year-dummies did not play an important role in each industry-specific model and the aggregate model was obviously based on UK quoted stock exchange companies. It only makes a marginal contribution to the industry-specific model.

10.10 Classification Accuracy Test

Three models (UR, IRR1, and IRR2) outperform the proportional chance model with respect to the percentage of expected cost estimated, regardless of various costs ratios. In general IRR1 model outperforms the UR and IRR2 models with respect to the relative costs both in chapter 7 (comparison the UR, IRR1, and IRR2) and chapter 8 (three different business cycles). This implies that decision makers may choose IRR1 model to minimize costs of misclassification.

In general misclassification of failed firms decreases and misclassification of non-failed firms increases when costs ratios increase and cut-off point shift from left to right. But in the three business cycle and each specific industry model, the misclassification of failed and non-failed firms under five different costs is not sensitive when compared to total sample perhaps due to more homogeneous financial characteristics. (see: chapter 8 Table 8-5, 8-10, 8-15 and Table 8-20, 8-25, 8-30), and chapter 9)

10.11 Implications

Industry relative (mean) ratios improved the predictive ability of the MDA method as compared to unadjusted ratios in general model and business cycle models. A possible illustration for the improvement is that the industry-relative transformation produced a stable variable and allowed direct comparison of companies over time and across industries. These results have direct implications for empirical research in a number of other application areas of both accounting and finance, such as the effects of merger and acquisitions on corporate performance and bond ratings.

Industry-specific models improved the predictive ability as compared to an aggregate model. Ideally, each specific industries suppose to have similar product related.

industry structure related, and financial related common characteristics. These results yield a more stable financial ratios than that of combined sample and their ratios allow for direct comparison of companies. In practice, the user of the failure prediction model needs to ensure that the sample used to derive the model has no companies biases because of change in SIC group compositions. It is possible that a failure prediction model developed from data for that industry and period will be biased by a incorrect SIC group if without taking into account industry properly.

Using industry relative ratios gives better predictive ability than that of unadjusted ratios. However, there are some problems one needs to heed. In theory, the firms of an industry should be homogeneous with similar operating characteristics. In practice, some industries contain firms that are much different, possibly because they also operate in other industries. For example, one company had 40% in broadcasting, 37% in electric appliances, and the remainder in paper industry. Firms may change their SIC group compositions because of business changes. To cope with the above problem, it seems that an alternative classification method which explicitly considers economic attributes of every business segment of a firm in specific industries may enhance the cross-sectional analysis of financial ratios. Focusing on two economic characteristics (1) The economic sector to which the segment's products are sold, and (2) the sensitivity of the segment to changes in business cycles [Amit and Livnat, 1990] may aid in dealing with this problem.

Due to industry/period specific effect, a homogeneous failure prediction model should be developed from specific industry for that economic phases in order to control for differences in the financial structure of firms in different industries across different economic environments. However, standard practice in failure prediction studies involves pooling data across different years so as to obtain a sufficiently large sample of failed firms for analysis. It is interest noted that failed firms in different industries are more or less affected by different business cycle phases if data is sufficient.

Ideally, a model developed for an industrial sector in one period is applied to the same sector in the other period to determine predictive accuracy outside the estimation period. Another model also developed for different industries in the same economic phase to evaluate the difference. If the size of sample is small, conclusion from such a small sample in that phase might not be generalizable.

Evidence from this study may provide insights useful in formulating public policy regarding interindustry and economic cycles policy. In addition, the study's empirical results may facilitate the formulation of better failure rate forecast. These forecast may assist government planning agencies and private investment advisers evaluate the unequal impacts of economic cycles on each different industries.

10.12 Future Work

As an largely empirical study, heavily dependent on prior literature, this work has not found much guidance from theory. Future work on failure/distress prediction ought to focus more directly upon the behaviour of the corporate failure process. Because failing firms may have different failure processes in terms of the behaviour of financial and non-financial ratios. For example, in the behaviour of financial ratios, Laitinen [1991] indicated that Argenti [1976, pp. 148-167] shows three alternative types of failure processes each of which is associated with different behaviour of financial ratios.

1 The first failure process follows a very low profile indicating that the performance of the firm never rises above poor before failing.

2 The second process hits upwards to fantastic heights before crashing down again.

3 The third process becomes interesting at the end of a period of good or excellent performance where there is a partial collapse. This collapse is followed by a plateau after which there is rapid decline to insolvency.

However, in the behaviour of non-financial ratios, the following studies have pointed out:

1 Storey, et al [1987] inferred that the age of companies was identified as an important variable in developing separate business failure process. Given the generally high rate of failure amongst young companies, it could be argued that failure prediction rates would be improved by developing failure process models for different age groups of companies. They show that some significantly different relationships exist and that young small firms perform very differently from old small firms. Qualitative information on a company is also broadly contained in their study. To develop this idea they are investigating whether factors such as (1) the characteristics of and changes in the ownership and management structure, (2) the financial reporting submission lags, (3) the incidence of audit qualifications and changes in auditors, and (4) the existence of loans secured on the company's assets, are consistently associated either with failure or non-failure.

2 The business failure is affected by the different processes of compulsory liquidation, voluntary liquidation or receivership. Molinero and Ezzamel [1991] suggested that it is possible that voluntarily liquidated firms have financial and organizational characteristics which are significantly different from those firms subject to compulsory liquidation and receivership. For example, Ghosh, et al [1991] displayed that a voluntary liquidation occurs when a corporation sells all assets, settles all outstanding claims, and distributes the residual to common stockholders as a liquidating dividend.

Analysis of such potential variables which are associated with the decision to voluntarily and compulsorily liquidate a company for failing and non-failing firms would be greatly useful in developing business failure process.

3. It is argued that information on director resignations or appointments have predictive ability with respect to the different failure process(es). For example, Peel, Peel, and Pope [1985] reported that resignations may mirror a company's dissatisfaction with the managerial performance of one or more of its board. This in turn may reflect dissatisfaction with company performance. Appointment, on the other hand, may indicate expanding operations or alternatively an attempt to strengthen the management team. (2) Director shareholdings: If directors are viewed as being in a privileged position with regard to price sensitive information then any change in directors' shareholdings may correct with impending good or bad news. (3) The time lag between a company's accounting financial year end and the date the annual accounts are actually published might vary in part with the contents of the accounts (good or bad news). Thus, changes in directors' non-beneficial shareholdings and changes in substantial shareholdings may also have predictive content in different failure processes according to ownership composition.

4. Finally, given the absence of an acceptable theory of failure/distress, a thorough understanding of the present processes used by human experts should be used to help inform model development, was suggested by Keasey and Watson [1991]. They indicated that human experts are able to access a wider range and variety of information inputs and to process it in a manner more suited to the specific decision context in question. They are also able to call upon the knowledge of other experts and to reach better decisions working collectively.

5. As an alternative to failure companies can be restructed by live-downs, spin-offs and mergers which may not lead to defaults on financial instruments.

Whereas, in this study, we have also examined the stability problem of time series and across industries according to the industry relative ratios, the state of the business cycle, and the industry-specific models. However, future work on failure/distress prediction may continue to focus on the other corporate failure processes and human experts which were discussed above.

Appendix A: Listing Financial Ratios in This Study

1. Profitability Ratios

R1=	(NI/TS)	Net Income / Sales	(175 / 104)
R2=	(FF/NW)	Funds Flow / Net Worth	(135 / 307)
R3=	(FF/TA)	Funds Flow / Total Assets	(135 / 339 + 356 + 376)
R4=	(NI/TA)	Net Income / Total Assets	(175 / 339 + 356 + 376)
R5=	(NI/NW)	Net Income / Net Worth	(175 / 307)
R6=	(EBIT/TS)	Earnings Before Interest and Tax / Sales	(144 + 137 / 104)
R7=	(NI/TL)	Net Income /Total Liability	(175 / 321 + 389)
R8=	(EBIT/TA)	EBIT / Total assets	(144+137) / (339+356+376)

2. Capital Turnover Ratios

R9=	(QA/TA)	Quick Assets / Total Assets	(375 + 370 / 339+356+376)
R10=	(FF/TS)	Funds Flows / Sales	(135 / 104)
R11=	(CA/TA)	Current Assets / Total Assets	(376 / (339+356+376)
R12=	(NW/TS)	Net Worth / Sales	(307 / 104)
R13=	(TS/TA)	Sales / Total Assets	(104 / 339 + 356 +376)
R14=	(WC/TA)	Working Capital/Total Assets	(390 / (339 +356 +376)

3. Financial Leverage

R15	= (TS/NPA)	Sales / Net Plant Assets	(104 / 328 - 336)
R16	= (TL/TA)	Total Liability / Total Assets	(322+389/339+356+376)
R17	= (TL/NW)	Total Liability / New Worth	(322 + 389 / 307)
R18	= (LTD/CA)	Long Term Debt/ Current Assets	(319 / 376)
R19	= (C.G.)	Capital Gearing	(306 + 321 + 309)/ (322 + 309 - 344)
R20	= (FF/CL)	Funds Flow/Current Liability	(135 / 389)
R21	= (RE/TA)	Retained Earning/Total Assets	(304 / 339 + 356 + 376)

Contd-

4. Liquidity Ratios

R22	= (TD/TC)	Total Debt / Total Capital	(318 + 319) / 322
R23	= (TD/TA)	Total Debt / Total Assets	(318 + 319) / (339 + 356 + 376)
R24	= (CA/CL)	Current Assets/Current Liability	(376 / 389)
R25	= (QA/CL)	Quick Assets / Current Liability	(375 + 370 / 389)
R26	= (CL/NW)	Current Liability / Net Worth	(389 / 307)
R27	= (CL/TA)	Current Liability / Total Assets	(389 / 339 +356 +376)
R28	= (CL/TL)	Current Liability/ Total Liability	(389 / 321+389)
R38	= (QA/TL)	Quick Assets / Total Liability	(375 + 370 / 321 + 389)

5. Cash Position

R29	= (TC/TS)	Cash / Sales	(375 / 104)
R30	= (TC/TA)	Cash / Total Assets	(375 / 339 +356 +376)
R31	= (TC/CL)	Cash / Current Liability	(375 / 389)

6. Inventory Turnover

R33	= (CA/TS)	Current Assets / Sales	(376 / 104)
R34	= (INV/TS)	Inventory / Sales	(364 / 104)
R35	= (TS/WC)	Sales / Working Capital	(104 / 390)

7. Receivable Turnover

R36	= (QA/INV)	Quick Assets / Inventory	(370 +375) / 364
R37	= (QA/TS)	Quick Assets / Sales	(370 +375) / 104

8. Other Ratios

R39	= (IC/TS)	Total Interest Charge / Sales	(153 / 104)
R40	= Log(TA)	Log (Total assets)	(339 + 356 + 376)
R41	= (OP/TP)	Operating Profit/Tax Profit	(137 / 175)
R42	= (IC)	Interest Coverage	(137 + 144 / 153)
R32	= ICR	Interval Credit Ratio (Current Assets-Stock-Current Liability) / (Sale - Dep.- Profit Before Tax)/ 365	

** Missing data (data not available)

Appendix A.1 Definitions of Ratio Components

NI	Net Income (175)
TS	Sales (104)
FF	Funds Flow (135)
NW	Net Worth (307)
TA	Total Assets (339 + 356 + 376)
EBIT	Earning Before Interest and Taxes (144 + 137)
TL	Total Liability (321 + 389)
QA	Quick Assets (370 +375)
CA	Current Assets (376)
WC	Working Capital (390)
NPA	Net Plant Assets (328 -336)
LTD	Long Term Debt (319)
C.G.	Capital Gearing (Preferred capital Plus Subordinated debt, total loan capital, borrowing repayable within 1 year divided by total capital employed plus borrowing repayable within 1 year, and total intangibles) (306 + 295 +321 +309) / (322 + 309 - 344)
TD	Total Debt (318 + 319)
TC	Total Capital (322)
RE	Retained Earnings (304)
CL	Current Liability (389)
INV	Inventory (364)
IC	Interest Charge (153)
OP	Adjusted Operating Profit (137)
TP	Adjusted After Tax Profit (175)
IC	Interest Coverage (137 + 144 / 153)

Appendix B: Key to Variable Definitions

Items	Definition
104 Total Sales	This amount of sales of goods and services to third parties, relating to the normal activities of the company. This amount does not include VAT or any other taxes relating directly to turnover, and will be net of trade discouts.
135 Trading Profit	This is the net profit derived from normal trading activities before depreciation, operating provisions and interest.
137 Operating Profit	This is net profit derived from the normal activities of the company after depreciation.
144 Total Non-operating Income	This includes dividend income, interest received, rents, grants and any other non-operating income.
153 Total Interest Charges	This shows interest on bank, covertible and other oans, bonds and debentures, leasing finance and hire purchase minus interest capitalised.
175 After Tax Profit	This shows the after tax profit, adjusted for items which do not relate to the normal trading activities of the company, net of adjusted tax.
304 Reserves	This is comprised of accumulated profit and loss account balances, general and capital reserves.
306 Preference Capital	This shows capital which has a fixed dividend and does not participate firther in the profits of the company.
307 Total Share Capital and Reserve	This shows the equity capital and reserves, including preference capital
309 Borrowings Repayable Within 1 Year	
318 Short-Term Loans	This shows all loan which are due within 5 years.
319 Long-Term Loans	This shows loans which are repayable in more than five years.
321 Total Loan Capital	This relates to all loans repayable in more than 1 year. Loans from group companies and associates are included.

Continue..

322 Total Capital Employed	This shows the sum of all non-current liabilities. It is equal to total assets
328 Plant and Machinery - Gross	Includes plant, machinery, motor vehicles, equipment, furniture and fittings, etc.
336 Plant and Machinery - Depreciation	This includes plant, machinery, equipment, motor vehicles, furniture and fittings.
339 Net Fixed Assets	This shows the net total of land and buildings, plant and machinery, construction in progress and any other fixed assets. Assets leased out are excluded. (Total gross fixed assets less total depreciation fixed assets)
344 Total Intangibles	This is comprised of items such as research and development, goodwill, patents, trade marks, etc.
356 Total Investment	This includes both short- and long-term investments, investment in associates, invstment properities, land and properties held for development, joint venture, partnerships and trusts.
364 Stock and W.I.P	This shows all stocks, raw materials, etc., plus work in progress less advances on work in progress.
370 Debtors & Equivalent	Accounts receivable after 1 year are included in this item, with the exact total debtors due in more than 1 year.
375 Cash and Equivalent	This includes cash, bank balances, etc., and short-term loans and deposits. It excludes short-term investments.
376 Current Assets	This includes stock, work in progress, debtors, cash and equivalent and any other current assets. Acccounts receivable after 1 year are included.
389 Current Liabilities	This includes current provisions, creditors, borrowings repayable within 1 year and any other current liabilities.
390 Net Current Assets	Trade accounts receivable and payable after 1 year are included. Short-term securities are excluded. (current assets less current liabilities)

Appendix C: Producing Industry Relative Ratios (Mean) Computer Program.

```
/*Scans the tidyed up datastream file and produces the mean */
/* for each ratio in each year                  */
TRACE OFF
address command
parse upper arg fn ft .
in_title = fn ft 'A'
out_title = fn '$'ft 'A'
'ERASE' out_title
NUMERIC DIGITS 13
nrecs = FILESIZE(in_title)
'EXECIO 1 DISKR' in_title '(VAR REC'
ratio = WORD(REC,1)
'EXECIO 1 DISKR' in_title '(VAR REC'
REC = OVERLAY('      ',REC,18,6)
'EXECIO 1 DISKW' out_title '0 F 80 (VAR REC'
recnum = 2
company. = ''
company.0 = 0
count = 0
do forever
  'EXECIO 1 DISKR' in_title '(VAR REC'
  if rc ^= 0 then LEAVE
  recnum = recnum+1
  if recnum // 250 = 0 then
    say TRUNC(recnum/nrecs*100)'% thru' in_title
  if WORDS(REC) = 1 then do
    str = WORD(REC,1)
    if SUBSTR(str,1,1) = 'R' then do
      str = SUBSTR(str,2)
      if DATATYPE(str,'W') then do
        company.0 = count
        CALL MEAN
```

Continue

```
        ratio = WORD(REC,1)
        'EXECIO 1 DISKR' in_title '(VAR REC'
        count = 0
        ITERATE
      end
    end
  end
  count = count+1
  company.count = REC
end
company.0 = count
CALL MEAN
'FINIS' in_title
'FINIS' out_title
EXIT 0
/* MEAN */
MEAN:
do i = 1 to company.0
parse upper var company.i   1 . 26 col.1 35 col.2 44 col.3 53 col.4 ,62 col.5 71 .
  do j = 1 to 5 col.j = SPACE(col.j,0)
    p = POS(',',col.j)
    if p > 0 then do
      col.j = DELSTR(col.j,p,1)
    end
    if col.j = '' then do
      col.i.j = ''
      ITERATE
    end
    l = LENGTH(col.j)
    if SUBSTR(col.j,l,1) = 'M' then do
      col.i.j = SUBSTR(col.j,1,l-1)*1000
      ITERATE
```

Continue

```
      end
      col.i.j = col.j+0
    end
  end
  do j = 1 to 5
    k = 0
    do i = 1 to company.0
      if col.i.j = '' then ITERATE
      k = k+1
      col.k.j = col.i.j
    end
    col.j = k
  end
  do j = 1 to 5
    total = col.1.j
    do i = 2 to col.j
      total = total+col.i.j
    end
    mean.j = total/col.j
    if mean.j > 999999 then mean.j = RIGHT(mean.j,9)
    else                    mean.j = FORMAT(mean.j,6,2)
  end
  RECORD = COPIES(' ',80)
  RECORD = OVERLAY(ratio,RECORD,1,9)
  RECORD = OVERLAY(mean.1,RECORD,26,9)
  RECORD = OVERLAY(mean.2,RECORD,35,9)
  RECORD = OVERLAY(mean.3,RECORD,44,9)
  RECORD = OVERLAY(mean.4,RECORD,53,9)
  RECORD = OVERLAY(mean.5,RECORD,62,9)
  'EXECIO 1 DISKW' out_title '(I F 80 (VAR RECORD'
  RETURN 0
```

```
/* Scans the tidyed up datastream file and produces the median */
/* for each ratio in each year                    */

TRACE OFF
address command
parse upper arg fn ft .
in_title = fn ft 'A'
out_title = fn '$'ft 'A'
'ERASE' out_title

NUMERIC DIGITS 13

nrecs = FILESIZE(in_title)

'EXECIO 1 DISKR' in_title '(VAR REC'
ratio = WORD(REC,1)

'EXECIO 1 DISKR' in_title '(VAR REC'
REC = OVERLAY('      ',REC,18,6)
'EXECIO 1 DISKW' out_title '0 F 80 (VAR REC'

recnum = 2
company. = ''
company.0 = 0
count = 0

do forever
   'EXECIO 1 DISKR' in_title '(VAR REC'
  if rc ^= 0 then LEAVE
  recnum = recnum+1

  if recnum // 250 = 0 then
    say TRUNC(recnum/nrecs*100)'% thru' in_title

  if WORDS(REC) = 1 then do
    str = WORD(REC,1)
    if SUBSTR(str,1,1) = 'R' then do
      str = SUBSTR(str,2)
      if DATATYPE(str,'W') then do
        company.0 = count
        CALL MEDIAN

        ratio = WORD(REC,1)
        'EXECIO 1 DISKR' in_title '(VAR REC'
        count = 0
        ITERATE
      end
    end
  end
```

....Continue

```
    count = count+1
    company.count = REC
  end

  company.0 = count
  CALL MEDIAN

  'FINIS' in_title
  'FINIS' out_title


  EXIT 0


  /* MEDIAN */
  MEDIAN:


  do i = 1 to company.0
    parse upper var company.i   1 . 26 col.1 35 col.2 44 col.3 53 col.4 . 62 col.5 71
    do j = 1 to 5 col.j = SPACE(col.j,0)


      p = POS(',',col.j)
      if p > 0 then do
        col.j = DELSTR(col.j,p,1)
      end


      if col.j = '' then do
        col.i.j = ''
        ITERATE
      end


      l = LENGTH(col.j)
      if SUBSTR(col.j,l,1) = 'M' then do
        col.i.j = SUBSTR(col.j,1,l-1)*1000
        ITERATE
      end


      col.i.j = col.j+0
    end
  end

  do j = 1 to 5
    k = 0
    do i = 1 to company.0
      if col.i.j = '' then ITERATE
```

Continue

```
    k = k+1
    col.k.j = col.i.j
  end
  col.j = k
end


do j = 1 to 5
  do i1 = 1 to col.j-1
    min = col.i1.j
    do i2 = i1+1 to col.j
      if col.i2.j > min then ITERATE
      col.i1.j = col.i2.j
      col.i2.j = min
      min = col.i1.j
    end
  end
end


do j = 1 to 5
  num = col.j
  if num // 2 = 0 then do
    i = num/2
    median.j = col.i.j
  end
  else do
    i = (num+1)/2
    median.j = col.i.j
  end
  if median.j > 999999 then median.j = RIGHT(median.j,9)
  else                      median.j = FORMAT(median.j,6,2)
end


RECORD = COPIES(' ',80)
RECORD = OVERLAY(ratio,RECORD,1,9)
RECORD = OVERLAY(median.1,RECORD,26,9)
RECORD = OVERLAY(median.2,RECORD,35,9)
RECORD = OVERLAY(median.3,RECORD,44,9)
RECORD = OVERLAY(median.4,RECORD,53,9)
RECORD = OVERLAY(median.5,RECORD,62,9)


EXECIO 1 DISKW' out_title '0 F 80 (VAR RECORD'


RETURN 0
```

Appendix E: Producing Industry-Specific Industry Relative Ratios

(1) Some Selected Industry Mean Ratios For Building Materials Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
2	YR1971	4.96	0.44	57.79	1.49	0.39
2	YR1972	5.92	0.41	55.86	1.52	0.38
2	YR1973	5.75	0.43	57.90	1.45	0.40
2	YR1974	4.36	0.42	56.69	1.43	0.39
2	YR1975	3.94	0.44	56.54	1.68	0.40
2	YR1976	4.38	0.47	57.74	1.67	0.41
2	YR1977	4.55	0.48	52.58	1.63	0.41
2	YR1978	4.48	0.48	49.77	1.67	0.41
2	YR1979	4.69	0.47	46.52	1.61	0.42
2	YR1980	4.20	0.46	42.96	1.68	0.42
2	YR1981	3.88	0.43	43.85	1.67	0.42
2	YR1982	3.36	0.42	45.91	1.53	0.42
2	YR1983	2.99	0.42	48.51	1.49	0.39
2	YR1984	3.71	0.43	50.44	1.52	0.39
2	YR1985	4.47	0.43	49.77	1.51	0.40

(1) Some Selected Industry Median Ratios For Building Materials Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
2	YR1971	4.62	0.53	54.00	1.57	0.40
2	YR1972	5.39	0.58	52.18	1.70	0.40
2	YR1973	5.00	0.57	55.98	1.65	0.42
2	YR1974	3.86	0.57	56.40	1.55	0.40
2	YR1975	3.23	0.60	56.49	1.68	0.41
2	YR1976	3.66	0.63	59.05	1.66	0.44
2	YR1977	3.11	0.67	58.69	1.72	0.42
2	YR1978	3.84	0.65	51.72	1.74	0.43
2	YR1979	3.74	0.64	53.20	1.62	0.42
2	YR1980	2.52	0.59	44.47	1.60	0.40
2	YR1981	2.16	0.59	43.94	1.70	0.41
2	YR1982	1.95	0.56	45.17	1.66	0.41
2	YR1983	2.68	0.58	47.89	1.62	0.41
2	YR1984	2.98	0.58	45.22	1.60	0.40
2	YR1985	3.28	0.58	45.22	1.50	0.40

(2) Some Selected Industry Mean Ratios For Contracting Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
3	YR1971	2.27	0.68	69.92	1.27	0.30
3	YR1972	3.58	0.70	67.67	1.40	0.38
3	YR1973	4.28	0.71	68.74	1.45	0.43
3	YR1974	3.27	0.71	69.32	1.46	0.43
3	YR1975	2.64	0.70	69.17	1.50	0.37
3	YR1976	2.91	0.69	70.34	1.51	0.39
3	YR1977	3.07	0.68	70.52	1.46	0.40
3	YR1978	3.18	0.66	60.24	1.58	0.43
3	YR1979	2.79	0.67	60.62	1.59	0.46
3	YR1980	2.05	0.66	57.26	1.55	0.41
3	YR1981	2.13	0.66	53.18	1.60	0.44
3	YR1982	2.29	0.64	53.86	1.50	0.46
3	YR1983	1.96	0.66	57.43	1.45	0.47
3	YR1984	2.24	0.66	57.87	1.44	0.46
3	YR1985	1.73	0.68	61.23	1.46	0.47

(2) Some Selected Industry Median Ratios For Contracting Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
3	YR1971	2.15	0.71	60.23	1.34	0.33
3	YR1972	2.45	0.71	59.01	1.49	0.35
3	YR1973	3.43	0.72	63.45	1.48	0.36
3	YR1974	3.19	0.72	65.73	1.42	0.39
3	YR1975	3.13	0.73	65.85	1.44	0.34
3	YR1976	2.88	0.71	67.37	1.51	0.35
3	YR1977	2.43	0.71	67.77	1.42	0.38
3	YR1978	2.88	0.72	65.94	1.47	0.39
3	YR1979	2.83	0.71	61.38	1.45	0.41
3	YR1980	2.39	0.71	60.71	1.39	0.36
3	YR1981	2.12	0.70	53.20	1.45	0.35
3	YR1982	1.97	0.68	54.77	1.40	0.45
3	YR1983	1.92	0.69	56.21	1.37	0.43
3	YR1984	2.14	0.71	58.07	1.33	0.42
3	YR1985	2.45	0.73	58.70	1.35	0.42

(3) Some Selected Industry Mean Ratios For Electricals Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
4	YR1971	3.48	0.63	57.68	1.90	0.53
4	YR1972	3.87	0.65	58.03	1.85	0.56
4	YR1973	4.12	0.65	57.85	1.77	0.54
4	YR1974	3.51	0.67	60.54	1.66	0.53
4	YR1975	3.57	0.67	60.31	1.82	0.51
4	YR1976	3.59	0.66	64.34	1.62	0.50
4	YR1977	3.59	0.68	62.08	1.66	0.49
4	YR1978	3.64	0.69	61.03	1.68	0.52
4	YR1979	3.21	0.69	59.36	1.57	0.53
4	YR1980	2.84	0.67	57.43	1.62	0.47
4	YR1981	2.14	0.68	58.63	1.62	0.49
4	YR1982	2.27	0.67	59.00	1.56	0.48
4	YR1983	2.38	0.67	58.33	1.64	0.47
4	YR1984	3.63	0.66	57.61	1.76	0.50
4	YR1985	3.43	0.66	56.27	1.84	0.48

(3) Some Selected Industry Median Ratios For Electricals Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
4	YR1971	3.48	0.63	57.68	1.90	0.53
4	YR1972	3.87	0.65	58.03	1.85	0.56
4	YR1973	4.12	0.65	57.85	1.77	0.54
4	YR1974	3.51	0.67	60.54	1.66	0.53
4	YR1975	3.57	0.67	60.31	1.82	0.51
4	YR1976	6.12	0.71	53.00	2.10	0.51
4	YR1977	4.65	0.68	51.69	1.86	0.48
4	YR1978	4.34	0.73	50.52	1.85	0.50
4	YR1979	4.00	0.70	42.74	1.80	0.51
4	YR1980	3.49	0.68	42.01	1.78	0.50
4	YR1981	2.83	0.68	38.05	2.03	0.51
4	YR1982	2.62	0.67	41.56	2.11	0.47
4	YR1983	3.69	0.68	40.49	1.89	0.49
4	YR1984	3.44	0.70	44.69	1.91	0.51
4	YR1985	4.82	0.71	43.06	1.63	0.47

(4) Some Selected Industry Mean Ratios For General-Engineering Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
7	YR1971	3.48	0.63	57.68	1.90	0.53
7	YR1972	3.87	0.65	58.03	1.85	0.56
7	YR1973	4.12	0.65	57.85	1.77	0.54
7	YR1974	3.51	0.67	60.54	1.66	0.53
7	YR1975	3.57	0.67	60.31	1.82	0.51
7	YR1976	3.80	0.69	60.60	1.83	0.53
7	YR1977	3.52	0.69	58.50	1.84	0.53
7	YR1978	3.41	0.70	57.56	1.80	0.53
7	YR1979	2.61	0.71	58.26	1.67	0.52
7	YR1980	2.03	0.69	55.51	1.68	0.49
7	YR1981	1.62	0.69	54.28	1.64	0.49
7	YR1982	1.46	0.69	55.32	1.66	0.50
7	YR1983	2.01	0.69	57.37	1.67	0.52
7	YR1984	2.57	0.70	58.58	1.64	0.50
7	YR1985	3.40	0.71	59.67	1.59	0.49

(4) Some Selected Industry Median Ratios For General-Engineering Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
7	YR1971	4.72	0.66	54.14	1.89	0.52
7	YR1972	4.80	0.68	48.66	1.89	0.53
7	YR1973	4.87	0.68	52.50	1.64	0.53
7	YR1974	4.33	0.70	54.53	1.64	0.54
7	YR1975	4.21	0.71	55.65	1.78	0.50
7	YR1976	4.10	0.73	56.68	1.76	0.53
7	YR1977	3.78	0.72	56.42	1.83	0.51
7	YR1978	4.03	0.72	52.81	1.90	0.51
7	YR1979	3.55	0.74	51.10	1.79	0.53
7	YR1980	2.49	0.72	49.15	1.81	0.51
7	YR1981	1.62	0.71	47.46	1.76	0.53
7	YR1982	1.95	0.71	49.30	1.75	0.52
7	YR1983	1.88	0.71	50.16	1.69	0.51
7	YR1984	2.92	0.71	50.92	1.61	0.51
7	YR1985	2.79	0.70	53.79	1.61	0.49

(5) Some Selected Industry Mean Ratios For Metals & Metal Forming Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
8	YR1976	2.31	0.76	69.49	1.57	0.57
8	YR1977	2.47	0.77	68.90	1.58	0.57
8	YR1978	2.41	0.79	68.48	1.55	0.61
8	YR1979	2.06	0.80	69.38	1.46	0.64
8	YR1980	1.81	0.86	74.24	1.31	0.83
8	YR1981	1.38	0.85	72.55	1.29	0.90
8	YR1982	1.50	0.84	73.36	1.24	1.09
8	YR1983	0.55	0.85	78.97	1.19	1.25
8	YR1984	1.09	0.67	58.49	1.60	0.37
8	YR1985	1.19	0.62	61.23	1.54	0.30

(5) Some Selected Industry Median Ratios For Metals & Metal Forming Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
8	YR1976	2.59	0.68	62.28	1.58	0.44
8	YR1977	2.61	0.69	59.87	1.69	0.43
8	YR1978	2.67	0.68	55.43	1.71	0.42
8	YR1979	2.57	0.69	53.09	1.62	0.47
8	YR1980	2.06	0.70	49.30	1.70	0.43
8	YR1981	0.18	0.68	49.00	1.71	0.48
8	YR1982	0.95	0.67	48.30	1.60	0.45
8	YR1983	1.27	0.66	51.12	1.60	0.43
8	YR1984	1.84	0.64	54.36	1.53	0.41
8	YR1985	2.58	0.68	54.35	1.47	0.39

(6) Some Selected Industry Mean Ratios for Motors Model

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
9	YR1971	3.75	0.57	50.08	1.88	0.47
9	YR1972	3.98	0.57	50.37	1.92	0.46
9	YR1973	3.62	0.58	54.86	1.69	0.46
9	YR1974	3.08	0.60	60.33	1.53	0.46
9	YR1975	2.52	0.56	57.35	1.67	0.43
9	YR1976	2.99	0.60	58.08	1.73	0.46
9	YR1977	2.79	0.60	51.76	1.77	0.44
9	YR1978	2.54	0.60	50.24	1.68	0.42
9	YR1979	2.33	0.63	54.47	1.61	0.43
9	YR1980	0.55	0.59	54.42	1.51	0.40
9	YR1981	-0.07	0.57	55.95	1.49	0.40
9	YR1982	0.62	0.58	59.27	1.43	0.39
9	YR1983	0.63	0.60	60.34	1.47	0.37
9	YR1984	1.72	0.61	61.65	1.42	0.37
9	YR1985	2.03	0.61	61.40	1.49	0.35

(6) Some Selected Industry Median Ratios for Motors Model

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
9	YR1971	4.10	0.60	56.88	1.47	0.41
9	YR1972	2.65	0.56	58.93	1.37	0.32
9	YR1973	2.32	0.58	57.96	1.41	0.36
9	YR1974	1.65	0.60	62.25	1.34	0.38
9	YR1975	1.64	0.59	63.38	1.31	0.35
9	YR1976	1.54	0.62	66.64	1.35	0.34
9	YR1977	2.12	0.63	64.03	1.44	0.32
9	YR1978	1.86	0.60	57.81	1.55	0.30
9	YR1979	1.59	0.61	58.55	1.45	0.32
9	YR1980	0.54	0.58	56.62	1.25	0.33
9	YR1981	0.17	0.58	57.28	1.25	0.30
9	YR1982	0.30	0.60	58.11	1.18	0.30
9	YR1983	0.53	0.60	57.77	1.24	0.28
9	YR1984	1.00	0.62	60.73	1.23	0.29
9	YR1985	1.35	0.62	61.91	1.29	0.25

(7) Some Selected Industry Mean Ratios For Brewers & Distillers Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
22	YR1976	3.45	0.32	60.48	1.13	0.25
22	YR1977	3.71	0.34	60.72	1.13	0.27
22	YR1978	3.87	0.36	49.52	1.12	0.28
22	YR1979	3.37	0.38	49.56	1.03	0.28
22	YR1980	3.22	0.33	45.24	1.19	0.27
22	YR1981	2.97	0.32	46.74	1.26	0.29
22	YR1982	2.98	0.33	44.95	1.29	0.28
22	YR1983	3.39	0.33	46.06	1.27	0.28
22	YR1984	3.96	0.33	46.53	1.29	0.28
22	YR1985	4.22	0.32	47.36	1.19	0.27

(7) Some Selected Industry Median Ratios For Brewers & Distillers Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
22	YR1976	4.73	0.30	40.34	1.39	0.25
22	YR1977	5.28	0.30	43.33	1.40	0.26
22	YR1978	4.94	0.31	40.77	1.38	0.27
22	YR1979	4.65	0.28	37.35	1.40	0.27
22	YR1980	4.39	0.28	34.52	1.30	0.26
22	YR1981	3.75	0.29	30.57	1.21	0.26
22	YR1982	4.65	0.25	30.63	1.19	0.28
22	YR1983	4.61	0.25	32.46	1.30	0.28
22	YR1984	5.21	0.26	37.03	1.16	0.28
22	YR1985	5.29	0.24	34.81	1.09	0.27

(8) Some Selected Industry Mean Ratios For Food Manufacturing Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
25	YR1976	2.64	0.64	63.35	1.74	0.30
25	YR1977	2.33	0.63	63.24	1.70	0.29
25	YR1978	2.30	0.62	63.27	1.68	0.30
25	YR1979	2.14	0.62	60.34	1.64	0.29
25	YR1980	1.98	0.61	60.92	1.52	0.27
25	YR1981	1.92	0.60	60.44	1.50	0.27
25	YR1982	2.04	0.58	60.64	1.47	0.26
25	YR1983	1.88	0.57	61.28	1.45	0.26
25	YR1984	2.08	0.56	60.01	1.40	0.26
25	YR1985	2.22	0.56	63.14	1.31	0.25

(8) Some Selected Industry Median Ratios For Food Manufacturing Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
25	YR1976	2.61	0.59	60.73	1.47	0.27
25	YR1977	2.32	0.61	60.11	1.42	0.27
25	YR1978	2.31	0.57	57.29	1.44	0.27
25	YR1979	2.45	0.60	56.11	1.49	0.30
25	YR1980	2.02	0.60	54.34	1.37	0.25
25	YR1981	2.08	0.59	54.86	1.43	0.25
25	YR1982	1.95	0.58	53.62	1.37	0.24
25	YR1983	1.56	0.57	52.82	1.34	0.25
25	YR1984	2.05	0.57	56.42	1.33	0.28
25	YR1985	2.09	0.58	56.91	1.32	0.26

(9) Some Selected Industry Mean Ratios for Food and Retailing Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
26	YR1976	1.57	0.40	56.82	0.97	0.12
26	YR1977	1.94	0.42	57.08	1.03	0.12
26	YR1978	1.60	0.44	48.83	1.04	0.12
26	YR1979	1.55	0.43	49.65	0.91	0.12
26	YR1980	1.60	0.43	54.67	0.82	0.12
26	YR1981	1.58	0.38	48.06	0.86	0.11
26	YR1982	1.67	0.37	49.68	0.82	0.11
26	YR1983	1.79	0.32	52.31	0.72	0.10
26	YR1984	2.02	0.32	55.84	0.68	0.10
26	YR1985	2.38	0.33	55.59	0.68	0.11

(9) Some Selected Industry Median Ratios for Food and Retailing Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
26	YR1976	1.47	0.43	57.11	0.78	0.13
26	YR1977	1.74	0.44	56.11	1.33	0.13
26	YR1978	1.68	0.44	49.32	1.24	0.13
26	YR1979	1.35	0.44	50.22	1.01	0.12
26	YR1980	1.40	0.32	53.23	0.72	0.13
26	YR1981	1.45	0.53	45.13	0.76	0.13
26	YR1982	1.34	0.46	56.35	0.72	0.15
26	YR1983	1.32	0.23	53.15	0.72	0.13
26	YR1984	2.34	0.42	53.36	0.78	0.12
26	YR1985	2.54	0.43	53.23	0.78	0.21

(10) Some Selected Industry Mean Ratios for Packing & Paper Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
31	YR1971	2.30	0.42	57.28	1.80	0.42
31	YR1972	2.44	0.49	63.16	1.58	0.40
31	YR1973	2.33	0.52	68.51	1.37	0.35
31	YR1974	2.50	0.58	71.15	1.53	0.36
31	YR1975	2.01	0.57	69.95	1.72	0.39
31	YR1976	2.22	0.61	71.41	1.67	0.39
31	YR1977	2.27	0.63	68.52	1.80	0.38
31	YR1978	2.63	0.62	65.94	1.69	0.40
31	YR1979	2.56	0.61	61.16	1.50	0.38
31	YR1980	1.99	0.59	61.08	1.46	0.36
31	YR1981	1.75	0.58	60.66	1.44	0.35
31	YR1982	1.89	0.58	60.24	1.52	0.38
31	YR1983	1.76	0.54	60.81	1.53	0.39
31	YR1984	1.54	0.55	64.72	1.63	0.40
31	YR1985	2.22	0.60	64.00	1.44	0.36

(10) Some Selected Industry Median Ratios for Packing & Paper Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
31	YR1971	3.14	0.55	55.01	1.67	0.43
31	YR1972	3.41	0.58	53.17	1.77	0.40
31	YR1973	4.22	0.60	54.64	1.84	0.46
31	YR1974	3.97	0.63	60.18	1.58	0.42
31	YR1975	3.60	0.65	59.45	1.75	0.38
31	YR1976	2.97	0.68	58.94	1.84	0.41
31	YR1977	2.85	0.66	55.61	1.86	0.41
31	YR1978	2.99	0.66	51.98	1.75	0.40
31	YR1979	2.72	0.62	54.22	1.54	0.41
31	YR1980	2.14	0.62	54.37	1.59	0.40
31	YR1981	0.98	0.63	53.37	1.52	0.39
31	YR1982	1.22	0.65	56.12	1.48	0.39
31	YR1983	1.48	0.64	55.79	1.42	0.38
31	YR1984	2.71	0.64	50.15	1.47	0.40
31	YR1985	2.66	0.62	53.94	1.50	0.38

(11) Some Selected Industry Mean Ratios for Stores Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
34	YR1976	4.08	0.49	46.19	1.80	0.34
34	YR1977	4.24	0.51	46.49	1.83	0.34
34	YR1978	4.31	0.52	45.09	1.82	0.34
34	YR1979	4.47	0.53	43.13	1.72	0.33
34	YR1980	3.88	0.52	41.94	1.64	0.31
34	YR1981	3.03	0.46	41.24	1.40	0.25
34	YR1982	3.27	0.41	37.00	1.37	0.25
34	YR1983	2.81	0.41	39.66	1.33	0.26
34	YR1984	3.62	0.41	39.57	1.30	0.25
34	YR1985	3.94	0.41	44.79	1.14	0.27

(11) Some Selected Industry Median Ratios for Stores Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
34	YR1976	3.47	0.62	55.86	1.57	0.47
34	YR1977	3.48	0.66	55.33	1.66	0.45
34	YR1978	3.46	0.68	49.71	1.65	0.42
34	YR1979	3.64	0.68	49.69	1.68	0.46
34	YR1980	3.08	0.64	49.89	1.62	0.41
34	YR1981	1.15	0.63	45.39	1.48	0.41
34	YR1982	1.45	0.64	46.89	1.50	0.40
34	YR1983	1.81	0.61	47.77	1.55	0.39
34	YR1984	2.08	0.60	45.68	1.48	0.39
34	YR1985	3.05	0.62	50.40	1.51	0.39

(12) Some Selected Industry Mean Ratios for Textiles Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
35	YR1971	3.05	0.61	52.81	1.81	0.51
35	YR1972	3.99	0.62	50.88	1.86	0.47
35	YR1973	4.92	0.67	53.22	1.81	0.48
35	YR1974	4.20	0.69	56.51	1.71	0.49
35	YR1975	2.38	0.68	57.92	1.75	0.47
35	YR1976	2.83	0.69	59.53	1.72	0.47
35	YR1977	3.12	0.72	57.64	1.80	0.46
35	YR1978	3.92	0.72	56.32	1.81	0.48
35	YR1979	3.51	0.71	53.59	1.74	0.49
35	YR1980	2.36	0.71	52.03	1.78	0.48
35	YR1981	1.35	0.68	49.81	1.74	0.47
35	YR1982	1.96	0.68	52.24	1.66	0.48
35	YR1983	2.07	0.66	50.18	1.72	0.47
35	YR1984	2.74	0.68	54.12	1.66	0.48
35	YR1985	3.17	0.69	55.27	1.68	0.46

(12) Some Selected Industry Median Ratios for Textiles Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
35	YR1971	3.03	0.66	48.39	1.72	0.52
35	YR1972	4.85	0.67	43.87	1.94	0.45
35	YR1973	5.38	0.69	50.32	1.85	0.45
35	YR1974	3.90	0.70	52.62	1.78	0.47
35	YR1975	2.43	0.69	53.04	1.76	0.43
35	YR1976	2.09	0.69	56.26	1.74	0.45
35	YR1977	3.10	0.73	54.01	1.89	0.44
35	YR1978	2.97	0.73	52.34	1.93	0.44
35	YR1979	2.99	0.74	50.54	1.90	0.46
35	YR1980	2.03	0.74	49.84	1.83	0.45
35	YR1981	1.23	0.73	45.38	1.82	0.44
35	YR1982	1.07	0.71	46.83	1.78	0.44
35	YR1983	1.51	0.70	43.79	1.76	0.42
35	YR1984	1.97	0.72	50.20	1.60	0.43
35	YR1985	2.38	0.72	50.33	1.62	0.41

(13) Some Selected Industry Mean Ratios for Chemicals Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
42	YR1971	4.70	0.44	59.18	1.91	0.56
42	YR1972	4.89	0.46	59.39	2.04	0.56
42	YR1973	6.41	0.51	59.77	2.11	0.60
42	YR1974	7.15	0.54	59.94	2.02	0.56
42	YR1975	5.67	0.52	59.35	2.07	0.56
42	YR1976	5.77	0.53	60.40	2.07	0.56
42	YR1977	4.95	0.52	57.20	2.09	0.50
42	YR1978	3.06	0.48	54.60	1.96	0.50
42	YR1979	3.89	0.47	52.27	1.88	0.47
42	YR1980	1.90	0.45	54.05	1.76	0.44
42	YR1981	1.96	0.47	56.43	1.67	0.47
42	YR1982	1.80	0.47	56.18	1.65	0.45
42	YR1983	3.07	0.48	55.22	1.71	0.44
42	YR1984	4.36	0.49	55.61	1.66	0.44
42	YR1985	4.22	0.51	56.07	1.63	0.42

(13) Some Selected Industry Median Ratios for Chemicals Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
42	YR1971	5.46	0.56	55.84	1.85	0.47
42	YR1972	5.02	0.56	53.28	1.65	0.46
42	YR1973	6.03	0.60	55.24	1.50	0.46
42	YR1974	5.03	0.61	61.03	1.45	0.45
42	YR1975	4.54	0.60	57.93	1.77	0.41
42	YR1976	4.75	0.60	60.05	1.68	0.43
42	YR1977	4.58	0.65	56.07	1.70	0.41
42	YR1978	3.72	0.58	53.68	1.72	0.43
42	YR1979	3.64	0.57	48.82	1.54	0.43
42	YR1980	2.49	0.56	45.09	1.68	0.41
42	YR1981	2.34	0.56	51.98	1.59	0.40
42	YR1982	2.13	0.61	53.86	1.49	0.42
42	YR1983	2.59	0.64	52.91	1.59	0.41
42	YR1984	3.02	0.65	55.11	1.59	0.45
42	YR1985	3.19	0.62	55.85	1.53	0.42

(14) Some Selected Industry Mean Ratios For Conglomerates Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
43	YR1971	2.76	0.52	68.05	1.26	0.40
43	YR1972	3.15	0.49	69.10	1.36	0.40
43	YR1973	3.50	0.44	69.89	1.24	0.38
43	YR1974	3.61	0.51	70.72	1.34	0.40
43	YR1975	3.16	0.56	70.24	1.33	0.44
43	YR1976	2.97	0.58	70.45	1.42	0.39
43	YR1977	2.84	0.56	66.74	1.42	0.36
43	YR1978	2.94	0.56	64.05	1.33	0.37
43	YR1979	2.65	0.57	62.94	1.37	0.39
43	YR1980	2.38	0.56	62.21	1.38	0.37
43	YR1981	1.92	0.58	65.81	1.42	0.41
43	YR1982	1.81	0.55	66.53	1.31	0.40
43	YR1983	2.10	0.57	65.42	1.32	0.41
43	YR1984	3.04	0.55	68.28	1.42	0.44
43	YR1985	3.81	0.59	61.03	1.58	0.48

(14) Some Selected Industry Meadian Ratios For Conglomerates Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
43	YR1971	2.75	0.52	66.22	1.51	0.47
43	YR1972	3.97	0.62	63.37	1.46	0.44
43	YR1973	3.72	0.57	68.76	1.27	0.44
43	YR1974	3.76	0.65	69.14	1.35	0.45
43	YR1975	2.85	0.63	66.80	1.47	0.41
43	YR1976	3.15	0.66	68.50	1.53	0.42
43	YR1977	3.07	0.67	61.71	1.65	0.40
43	YR1978	3.02	0.70	61.07	1.66	0.43
43	YR1979	2.71	0.70	63.30	1.49	0.46
43	YR1980	1.82	0.64	62.24	1.54	0.36
43	YR1981	1.74	0.61	61.16	1.46	0.42
43	YR1982	1.47	0.60	63.89	1.43	0.43
43	YR1983	2.07	0.61	60.47	1.34	0.42
43	YR1984	3.28	0.62	63.57	1.27	0.40
43	YR1985	3.77	0.58	56.77	1.40	0.43

(15) Some Selected Industry Mean Ratios For Transport Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
44	YR1976	3.16	0.34	61.48	1.14	0.41
44	YR1977	2.80	0.32	59.96	1.06	0.33
44	YR1978	1.26	0.32	59.70	1.00	0.30
44	YR1979	1.72	0.34	56.41	1.10	0.29
44	YR1980	1.67	0.36	56.65	1.04	0.23
44	YR1981	1.69	0.36	57.22	1.04	0.24
44	YR1982	1.14	0.36	58.87	1.00	0.20
44	YR1983	0.67	0.40	64.67	1.03	0.20
44	YR1984	0.84	0.44	59.42	1.07	0.18
44	YR1985	1.10	0.37	56.23	1.09	0.15

(15) Some Selected Industry Median Ratios For Transport Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
44	YR1976	5.92	0.33	60.31	1.38	0.47
44	YR1977	3.78	0.24	57.28	1.23	0.36
44	YR1978	2.09	0.24	49.35	1.30	0.30
44	YR1979	1.93	0.29	51.16	1.21	0.46
44	YR1980	4.06	0.30	48.20	1.14	0.36
44	YR1981	2.44	0.32	43.80	1.36	0.37
44	YR1982	1.39	0.34	57.35	1.27	0.36
44	YR1983	2.47	0.34	49.40	1.26	0.27
44	YR1984	1.67	0.32	47.86	1.30	0.26
44	YR1985	3.69	0.30	54.58	1.21	0.31

(16) Some Selected Industry Mean Ratios For Miscellaneous Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
48	YR1971	7.48	0.67	46.64	2.36	0.75
48	YR1972	7.55	0.67	46.11	2.27	0.74
48	YR1973	7.14	0.64	52.40	1.79	0.68
48	YR1974	4.27	0.67	62.98	1.75	0.51
48	YR1975	4.01	0.66	64.09	1.98	0.51
48	YR1976	2.95	0.65	62.27	1.97	0.36
48	YR1977	3.36	0.65	62.40	1.93	0.35
48	YR1978	3.18	0.65	59.44	1.76	0.36
48	YR1979	3.46	0.65	61.43	1.65	0.43
48	YR1980	2.92	0.63	59.96	1.60	0.39
48	YR1981	2.49	0.62	60.12	1.56	0.39
48	YR1982	3.05	0.63	58.61	1.67	0.39
48	YR1983	3.16	0.63	60.30	1.65	0.40
48	YR1984	3.30	0.61	57.69	1.69	0.36
48	YR1985	4.86	0.57	64.02	1.68	0.40

(16) Some Selected Industry Median Ratios For Miscellaneous Sector

INDUS	YEAR	NI/TS	CA/TA	TL/TA	CA/CL	CA/TS
48	YR1971	5.66	0.67	44.29	1.98	0.48
48	YR1972	7.12	0.67	44.82	1.86	0.44
48	YR1973	7.13	0.66	45.47	1.83	0.42
48	YR1974	5.36	0.66	48.97	1.66	0.44
48	YR1975	4.92	0.69	51.20	2.00	0.43
48	YR1976	4.63	0.71	52.16	2.00	0.43
48	YR1977	4.68	0.71	51.35	2.03	0.42
48	YR1978	3.93	0.71	47.65	1.84	0.43
48	YR1979	3.93	0.71	45.34	1.90	0.45
48	YR1980	2.96	0.68	42.34	1.78	0.44
48	YR1981	2.23	0.67	44.19	1.79	0.43
48	YR1982	2.92	0.65	42.68	1.61	0.40
48	YR1983	3.35	0.64	45.82	1.90	0.41
48	YR1984	3.41	0.66	52.94	1.74	0.42
48	YR1985	4.04	0.69	56.96	1.55	0.46

Appendix F: Datastream Industry Adjustment Firms

Code	Level 3	Level 5	Total Firms
BLDNG	Building Materials	Builders' Materials Building Mats	30
CONTR	Contracting	Housebuilding Construction	45
ELTCA	Electricals	Electrical Plant General Electrical Equipment	25
ENGEN	Engineering	Industrial Plant Mech.HAndling Pumps & Valves Steel $ Chem.Plant Wire & Ropes MIsc.Mech_Engg Machine & Other Tools	87
METFM	Metals & Metal Forming	Metallurgy Steel Misc.Metal Forming	33
MOTGP	Motors	Motor Components Motor Distributions Motor Vehicles	33
BRDIS	Brewers & Distillers	Breweries Wines & Spirits	32
FDMFG	Food Manafacturing	Processfd Foods Sugar Confectionery Milling & Flour	30
PKPAP	Packaging & Paper	Packaging & Paper	21
MEDI	Media	Broadcasting Media Agencies	37
STORE	Stores	Department Stores Furnishing Stores MAil order Multiple Stores	50
TEXTL	Textiles	Floor Covering Clothing Cotton & Synthetic Wool Misc.Textiles	60
CHMCL	Chemicals	General Chemicals Plastic & Rubber	19
CONGL	Conglomerates	Conglomerates	21
TRNSP	Transport	Shipping Transporting & Freight Bus & Coach serv. Railways Airlines	16
MISCS	Miscellaneous	Furnishure & Furns Household Appl. Kitchen & Table Security & Alarms Tobacco Leather & Footwear Giftware Office Equipment	61

Appendix G: Non-Failed Firm's Names

Code	Year	Non-Failed Firm Name	Code	Year	Non-Failed Firm Name
2	1977	BRIT. FITTINGS	9	1979	E.R.F.HOLDINGS
2	1977	CAKEBREAD,ROBEY	9	1981	APPLEYARD GROUP
2	1980	GIBBS & DANDY	9	1981	PLAXTON GROUP
2	1980	SHARPE & FISHER	9	1982	JESSUPS
2	1981	MARSHALLS	9	1982	WILLIAM JACKS
2	1981	NEWMAN-TONKS	9	1984	ABBEY PANELS INV
3	1974	CREST NICHOLSON	9	1984	EDBRO
3	1974	DOUGLAS,ROBERT M	9	1984	GATES,FRANK G.
3	1975	GLEESON,M.J.	9	1984	KWIK-FIT
3	1975	TILBURY	22	1983	CLARK,MATTHEW
3	1978	BOOTH INDUSTRIES	22	1983	MACALLAN-GLENLIVET
3	1978	WIGGINS GROUP	25	1980	A.G. BARR
3	1980	WARD HOLDINGS	25	1980	MATHEWS, BERNARD
3	1980	WILSON (CONNOLLY)	25	1983	HAZLEWOOD FOODS
3	1981	BRAITHWAITE	25	1983	BUSBORNE
3	1981	HEWDEN-STUART	31	1979	API GROUP
3	1982	BRITISH BLDG & EN	31	1979	BLAGDEN INDUSTRIES
3	1982	HOWARD HOLDINGS	31	1982	BLADGEN INDUSTRIES
3	1983	COUNTRYSIDE PROP	31	1982	FINLAY PACKAGIN
3	1983	FALCON INDUS	32	1980	HTV GROUP
3	1984	BEN BAILEY CONSTR	32	1980	WATMOUGHS HOLDINGS
3	1984	LAWRENCE,WALTER	32	1981	GEERS GROSS
4	1976	BEALES HUNTER	32	1981	GRAMPIAN TELE
4	1976	LEC REFRIGERATION	32	1981	MORE O'FERRALL
4	1983	BULGIN, A.F.	32	1981	WPP GROUP
4	1983	DOWDING & MILLS	32	1984	EMAP
7	1974	ADWEST	32	1984	SCOTTISH T.V.
7	1974	FENNER	34	1980	COURTS (FURN.)
7	1978	BROOKE TOOL ENG	34	1980	FORTNUM & MASON
7	1978	BSS GROUP	34	1980	LIBERTY & CO
7	1978	CARCLO ENGINEER	34	1980	OWEN & ROBINSON
7	1978	HILL & SMITH HOLD	34	1983	CHURCH & CO.
7	1978	METALRAX HOLDINGS	34	1983	HELENE
7	1978	ROTORK	34	1983	MOSS BROS GROUP
7	1980	ELLIOTT,B	34	1983	OLIVER GROUP
7	1980	MOLINS	34	1985	BEATTIE,JAMES
7	1983	ADWEST	34	1985	ELYS (WIMBLEDON)
7	1983	DOBSON PARK INDS	35	1975	CORAH
7	1983	HADEN MACLELLAN	35	1975	HOUSE OF LEROSE
7	1983	HALL ENGINEERING	35	1975	MACKAY, HUGH
7	1983	MOLINS	35	1975	PITTARD GARNAR
7	1983	TEX HOLDINGS	35	1976	MACKAY, HUGH
7	1984	BM GROUP	35	1976	YOUGHAL CARPETS
7	1984	POWERSCREEN	35	1977	LAWTEX
8	1983	LEE, ARTHUR	35	1977	TOWLES
8	1983	SAVILLE GORDON	35	1979	ATKINS HOSIERY
8	1984	COOPER FREDERICK	35	1979	BRITISH MOHAIR
8	1984	GARTON ENGINEER	35	1979	CONRAD CONT
8	1985	BRASWAY	35	1979	G.R. HOLDINGS
8	1985	CASTINGS	35	1979	GASKELL PLC
8	1985	CHAMBERLIN & HILL	35	1979	PARKLAND TEXTILES
8	1985	RADIANT METAL	35	1980	FRENCH, THOMAS
9	1979	BURNDENE INVS	35	1980	DAVENPORT KNITWEAR

Code	Year	Non-Failed Firm Name
35	1980	REXMORE
35	1980	SEET
35	1980	SHILOH
35	1980	STODDARD HDGS.
35	1980	TOMKINSONS
35	1980	VICTORIA CARPETS
35	1980	VIVAT HOLDINGS
35	1980	WORTHINGTON, A.J.
35	1980	YORKLYDE
35	1981	BECKMAN, A.
35	1981	CASKET
35	1981	LESLIE WISE GROUP
35	1981	RAMAR TEXTILES
35	1981	S. LYLES
35	1981	STIRLING GROUP
35	1982	ALLIED TEXTILE COS.
35	1982	AMBER DAY
35	1982	DEWHIRST,I.J.
35	1982	LEEDS GROUP
35	1982	PALMA GROUP
35	1982	READICUT INTL.
35	1983	BAIRD,WILLIAM
35	1983	HICKING,PENTECOST
35	1983	HOLLAS GROUP
35	1983	RICHARDS
35	1984	FORMINSTER
35	1984	FOSTER,JOHN
35	1984	HAWTIN
35	1984	MARLING INDU
39	1980	JAMES HALSTEAD
42	1979	ELLIS & EVERARD
42	1979	LEIGH INTERESTS
42	1980	PLYSU
42	1980	THURGAR BARDEX
42	1981	BTP
42	1981	CANNING,W
43	1977	BODYCOTE INTERNATI
43	1977	SALE TILNEY
44	1984	JOHN I. JACOBS
44	1984	OCEAN WILSONS
44	1985	DAVIES & NEWMAN
44	1985	FISHER,JAMES
48	1978	FUTURA HOLDINGS
48	1978	USHER WALKER
48	1980	ARTHUR WOOD
48	1980	CRT GROUP
48	1980	FERRY PICKERING
48	1980	LAMBERT HOWARTH
48	1980	PITTARD GARNAR
48	1980	PRESTIGE GROUP
48	1980	RELYON
48	1980	RICARDO INTL.
48	1981	ATTWOODS
48	1981	BLACK ARROW
48	1981	BLACK,PETER
48	1981	DELANEY GROUP
48	1981	J.W. SPEAR
48	1981	PLATIGNUM
48	1981	SIDNEY C. BANKS
48	1981	SILENTNIGHT HOL.
48	1982	ASTRA HOLDINGS
48	1982	ELBIEF
48	1982	STONEHILL HOL.
48	1982	TIME PRODUCTS
48	1983	CORNWELL PARK.
48	1983	COWAN,DE GROOT
48	1983	COFFICE & ELEC.
48	1983	SAMUEL HEATH
48	1983	STAG FURNITURE
48	1983	TOYE & COMPANY

Appendix H: Failed Firms Names

Code	Year	Failed Firm Name
2	1977	MCNEILL GROUP LTD
2	1980	FINDLAY HARDWARE
2	1981	CARRON HLDGS
3	1974	NORTHERN DEVELOPMENT
3	1975	IRELAND, ERNEST
3	1978	SOUTHERN CONSTR
3	1980	RICHARDS& WALNGTN
3	1981	CHANGE WARES
3	1982	MODERN ENGINEERS BRTL
3	1983	CROUCH GROUP
3	1984	COCKSEDGE HLDGS
4	1976	DIMPLEX INDUSTRIES
4	1983	DERRITRON
7	1974	HERBERT, ALFRED
7	1978	FAIRBAIRN LAWSON
7	1978	GEN ENGG.(RADCLIFF
7	1978	WILSON WALTON
7	1980	STONE-PLATT INDS
7	1983	ACROW
7	1983	CAPPER-NEILL
7	1983	DENNIS,JAMES H.
7	1984	ALLEN,W.G.(TIPTON)
8	1983	DANKS GOWERTON
8	1984	FARMER S W GRP
8	1985	CASTLE (G.B.)
8	1985	METAL SCIENCES
9	1979	FODENS
9	1981	CARAVANS INTERN
9	1982	PENNINE COMMERC
9	1984	HERMAN SMITH
9	1984	SOLEX
22	1983	TOMATIN DISTILL
25	1980	LOCKWOODS FOODS
25	1983	SCOTCROS
31	1979	INVERESK GROUP LTD
31	1982	MELODY MILLS
32	1980	OXLEY PRINTING
32	1981	DEANSON HLDGS
32	1981	WYATT WOODROW
32	1984	PITMAN
34	1980	MAPLE & CO. HOLDIN
34	1980	MICHAEL,JOHN
34	1983	BAMBER STORES
34	1983	SCAN DATA INT'L
34	1985	PETERS STORES
35	1975	HIGHLIGHT SPORTS
35	1975	HOUSE OF SEARS
35	1976	WORTH, BOND,
35	1977	STAFLEX INTERN
35	1979	BRIGRAY GROUP
35	1979	COPE SPORTSWEAR
35	1979	RIVINGTON REED
35	1980	BLACKWOOD,MORTON
35	1980	BOND STR FABRICS
35	1980	HOMFRAY CARPETS
35	1980	PICKLES,WILLIAM
35	1980	WILLIAMS, BEN
35	1980	YORKS.FINE WOOL
35	1981	BRITISH ENKALON
35	1981	CAWDAW IND HLDGS
35	1981	PAWSON W.L.
35	1982	B. PARADISE
35	1982	MELLINS
35	1982	PULLMAN,R &J
35	1983	ELLENROAD MILL
35	1983	SPENCER, GEORGE
35	1984	INTER-CITY INVEST
35	1984	NOVA(JERSEY)KNIT
42	1979	BURRELL & CO
42	1980	MOVITEX LIMITED
42	1981	ALNERY NO. 152
43	1977	BRITTAINS
44	1984	REARDON SMITH
44	1985	LYLE SHIPPING
48	1978	LIDEN (HOLDINGS)
48	1980	GOLDMAN, H
48	1980	P.M.A. HLDGS
48	1980	VINERS
48	1980	WHITELEY, B.S
48	1981	AUSTIN,F. LEYTON
48	1981	BERWICK TIMPO
48	1981	GRIMSHAWE HOLDINGS
48	1981	LESNEY PRODUCTS
48	1982	HIGHGATE OPTICAL
48	1982	METTOY
48	1983	AIRFIX
48	1983	BARGET
48	1983	METAMEC JENTIQUE

Appendix I: Outliers Removal Computer Program

```
%inc CHOU;
data LIN264;
  set LININDUS.SET;
 D1=input(put(cnum,CHOU.),8.);
  YEAR= _NAME_ ;
RUN;
PROC SORT DATA = LIN264     OUT=AF2;
  BY D1 ;
RUN;
 proc means data = AF2        mean std;
    BY D1;
 var R1-R42;
   output out = mean.list;
run;
data mean.list;
   set mean.list;
   drop _type_ _freq_;
   if _stat_ = 'MEAN' or _stat_ = 'STD';
run;
proc transpose data = mean.list out = mean.trans;
  BY D1;
run;
proc datasets library = mean;
   modify  trans;
   rename col1 = mean  col2 = std;
run;
data mean.trans;
   set mean.trans,
IF D1=0 THEN  lr2 = mean - (4*std);
IF D1=0 THEN  lr1 = mean - (2.5*std);
IF D1=1 THEN  lr4 = mean - (4*std);
IF D1=1 THEN  lr3 = mean - (2.5*std);
IF D1=0 THEN  up2 = mean + (4*std);
IF D1=0 THEN  up1 = mean + (2.5*std);
IF D1=1 THEN  up4 = mean + (4*std);
IF D1=1 THEN  up3 = mean + (2.5*std);
run;
```

Continue

```
proc sort data=mean.trans;
  by d1 ;
run;
%inc CHOU;
data INDUS264.NEW (DROP=_NAME_);
   set lin264;
 D1=input(put(cnum,CHOU.),8.);
   drop i up1 up2 up3 up4 lr1 lr2 lr3 lr4 mean std;
   array aline(42) R1-R42;
   do i = 1 to 42;
     marker = i;
     set mean.trans point = marker;
     if D1=0 AND aline(i) < lr1 then do;
     if D1=0 AND aline(i) <lr2 then aline(i) = mean;
        else aline(i) = lr1;
        end;
     if D1=0 and aline(i) > up1 then do;mean;
        else aline(i) = up1;
        end;
     if D1=1 AND aline(i) < lr3 then do;
     if D1=1 AND aline(i) <lr4 then aline(i) = mean;
        else aline(i) = lr3;
        end;
     if D1=1 AND aline(i) > up3 then do;
     if D1=1 AND aline(i) >up4 then aline(i) = mean;
        else aline(i) = up3;
     end;
  end;
run;
```

```
/*proc print; run;    */
   %inc hpopts;
 goptions nodisplay;
 proc greplay nofs
    igout = lin.gcat;
    delete _all_;
    quit;
run;

OPTIONS LS=76 NOTES ;

%INC chou;
data lin264.set;
   SET lin264.set;
   year = _name_;
 D1 = INPUT(PUT(CNUM,chou.),8.);
PROC SORT DATA=lin264.set OUT =AF2.sorted;
  BY D1 year;
  RUN;
 proc summary data = af2.sorted;
  var r1-r31 r33-r42;
  by D1 year;
  output out = results mean= r1 -r31 r33-r42;
run;
 proc print; run;
 data results;
  set results;
  drop _type_ _freq_ d1;
run;
PROC SORT DATA=results OUT =res;
  BY year;
  RUN;
proc transpose data = res out = trans name= cname prefix=d;
  by  year;
RUN;
 proc print; run;

 data trans;
  set trans;
  d0 = d1; d1 = d2;
  drop d2 ;
run;
proc sort data = trans out = plot.set1;
  by cname;
run;
 %inc hpopts;
goptions
      fby = simplex
      cby = black
      hby = 1.5
```

Continue

```
        goutmode = append
        gouttype = independent
        nodisplay;

TITLE1 h=1 F=SIMPLEX J=C 'COMPARISION OF FAILED AND NONFAILED
FIRMS';
TITLE2 h=1 F=SIMPLEX  J=C  'PROFILE ANALYSIS';
TITLE3 h=1 F=SIMPLEX  J=C  '% OF RATIOS ';
proc gslide gout = lin.gcat; run;
title;
FOOTNOTE J=l  'SOURCE:'
M=(8,+0)'THIS STUDY Red=NF Blue=F';
proc gslide gout = lin.gcat; run;
title; footnote;

PROC GPLOT DATA= plot.set1 gout = lin.gcat;
  by cname;
  label cname = '00'x;

AXIS1   VALUE=(F=SIMPLEX  H=1.5)
      LABEL= (f = simplex h= 1.5 'MEAN')
      MINOR = NONE;

AXIS2 VALUE=(F=SIMPLEX H=1.5 'YR5''-YR4''-YR3''-YR2''-YR1')
  Order = ('YR5' 'YR4' 'YR3' 'YR2' 'YR1')
  LABEL = (F=SIMPLEX H=1.5 'YEARS PRIOR TO FAILURE');

SYMBOL1 I=J  V=SQUARE  C=RED  h=2;
SYMBOL2 I=J  V=triangle C=blue   h=2;
    plot d0 * year
        d1 * year / overlay
                frame
                VAXIS = AXIS1
                HAXIS = AXIS2;
RUN;
%inc hpopts;
goptions  gtype = dependent display;
proc greplay    /* replay catalog matched to template */
   igout = lin.gcat
   tc = lin.templt
   template = sixteen
   nofs;
treplay 1:1 2:1 3:3 4:14 5:25 6:36 7:40 8:41 9:42 10:43
  11:44 12:4 13:5 14:6 15:7 16:8  17:9 18:10 19:2 20:2;
   quit;
run;
cms susplot hp;
proc greplay   /* replay catalog matched to template */
   igout = lin.gcat
   tc = lin.templt
   template = sixteen
   nofs;
```

Continue

```
Treplay 1:1 2:1 3:11 4:12 5:13 6:15 7:16 8:17 9:18 10:19
11:20 12:21 13:22 14:23  15:24  16:26 17:27 18:28 19:2 20:2;
   quit;
run;

cms SASPLOT HP;

proc greplay   /* replay catalog matched to template */
   igout = lin.gcat
   tc = lin.templt
   template = sixteen
   nofs;


treplay 1:1 2:1 3:29 4:30 5:31 6:32 7:33 8:34 9:35 10:37 11:38 12:39 19:2 20:2;
   quit;
run;

%inc hpopts;
eproc greplay tc = lin.templt nofs;
   tdef sixteen des = '16 rectangles plus 2 headings'

   /* define panel 1 - left heading */
   1/ llx = 0    lly = 50
     ulx = 0    uly = 100
     urx = 50   ury = 100
     lrx = 50   lry = 50

   /* define panel 2 - rightheading */
   2/ llx = 50    lly = 50
     ulx = 50    uly = 100
     urx = 100   ury = 100
     lrx = 100   lry = 50

   /* define panel 19 - left footing */
   19/ llx = 0    lly = 0
     ulx = 0    uly = 50
     urx = 50   ury = 50
     lrx = 50   lry = 0

   /* define panel 20 - right footing */
   20/ llx = 50    lly = 0
     ulx = 50    uly = 50
     urx = 100   ury = 50
     lrx = 100   lry = 0

   /* define panel 3  */
   3/ llx = 5    lly = 71
     ulx = 5    uly = 93
     urx = 20   ury = 93
     lrx = 20   lry = 71
```

Continue

```
/* define panel 4 */
4/ llx = 5    lly = 49
   ulx = 5    uly = 71
   urx = 20   ury = 71
   lrx = 20   lry = 49


/* define panel 5 */
5/ llx = 5    lly = 27
   ulx = 5    uly = 49
   urx = 20   ury = 49
   lrx = 20   lry = 27


/* define panel 6 */
6/ llx = 5    lly = 5
   ulx = 5    uly = 27
   urx = 20   ury = 27
   lrx = 20   lry = 5


/* define panel 7 */
7/ llx = 30   lly = 71
   ulx = 30   uly = 93
   urx = 45   ury = 93
   lrx = 45   lry = 71


/* define panel 8 */
8/ llx = 30   lly = 49
   ulx = 30   uly = 71
   urx = 45   ury = 71
   lrx = 45   lry = 49


/* define panel 9 */
9/ llx = 30   lly = 27
   ulx = 30   uly = 49
   urx = 45   ury = 49
   lrx = 45   lry = 27


/* define panel 10 */
10/ llx = 30  lly = 5
   ulx = 30   uly = 27
   urx = 45   ury = 27
   lrx = 45   lry = 5


/* define panel 11 */
11/ llx = 55  lly = 71
   ulx = 55   uly = 93
   urx = 70   ury = 93
   lrx = 70   lry = 71
```

Continue

```
 /* define panel 12 */
12/ llx = 55  lly = 49
    ulx = 55  uly = 71
    urx = 70  ury = 71
    lrx = 70  lry = 49

 /* define panel 13 */
13/ llx = 55  lly = 27
    ulx = 55  uly = 49
    urx = 70  ury = 49
    lrx = 70  lry = 27

 /* define panel 14 */
14/ llx = 55  lly = 5
    ulx = 55  uly = 27
    urx = 70  ury = 27
    lrx = 70  lry = 5



 /* define panel 15 */
15/ llx = 80  lly = 71
    ulx = 80  uly = 93
    urx = 95  ury = 93
    lrx = 95  lry = 71

 /* define panel 16 */
16/ llx = 80  lly = 49
    ulx = 80  uly = 71
    urx = 95  ury = 71
    lrx = 95  lry = 49

 /* define panel 17 */
17/ llx = 80  lly = 27
    ulx = 80  uly = 49
    urx = 95  ury = 49
    lrx = 95  lry = 27

 /* define panel 18 */
18/ llx = 80  lly = 5
    ulx = 80  uly = 27
    urx = 95  ury = 27
    lrx = 95  lry = 5
;

run;
```

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